THE PREVALENCE AND INCREMENTAL COSTS OF HEALTHCARE ASSOCIATED INFECTIONS FOR INDIVIDUALS ADMITTED FOR POTENTIALLY PREVENTABLE HOSPITALIZATION

A Dissertation

by

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ABSTRACT

Since there is a limited literature base concerning individuals admitted with a potentially preventable hospitalization (PPH) who acquired a healthcare associated infection (HAI), this research identified the prevalence and costs of individuals admitted to Texas hospitals in 2011 for a PPH and acquired an HAI. Based on IOM identified associations between PPH and uninsurance, the analytic evaluation draws from theoretical models that link insurance status to outcomes such as PPH. Using the hypothesis that the cost of preventive care for the uninsured with ambulatory care sensitive conditions (ACSC) that lead to PPH would be less than the incremental cost of healthcare for HAI in individuals admitted with a PPH and acquired an HAI, I estimated costs for ACSC related preventive care, PPH, and the incremental cost of HAI. The Agency for Healthcare Research and Quality (AHRQ) Quality Indicator modules identified PPH using administrative inpatient discharge data and private insurer claims data. Adjusting for demographic, community and hospital characteristics, logistic regression analysis estimated odds ratios of PPH individuals acquiring an HAI, and generalized least squared regression estimated costs needed to address the hypothesis. I identified 1,031 individuals in the 2011 Texas inpatient discharge data with both a PPH and an HAI. 66% of the PPH with HAI population identified Medicare as their primary payer, and 7% identified Self-pay or Charity as primary payer. Most PPH individuals had lower odds of acquiring an HAI. However, individuals admitted with diabetes related lower extremity amputation demonstrated a significantly higher odds of acquiring either *Clostridium difficile* infection (OR: 2.9, $CI_{95\%}$ 2.16, 3.91) or ventilator

associated pneumonia (OR: 1.4, $CI_{95\%}$ 0.95, 2.18). The adjusted mean cost per hospitalization for PPH was approximately $2,000 less than the general inpatient population. The estimated incremental cost of HAI for the 97 uninsured individuals in the PPH and HAI population was $2.1 million. The cost of preventive healthcare for uninsured individuals in Texas with an ACSC was estimated at $66.8 billion. Given the large proportion of insured within the PPH with HAI population, and the incremental cost of HAI quantified, I recommend additional research focusing on the Medicare population affected.

DEDICATION

I would like to dedicate my dissertation to my husband and two sons whose unwavering love and support required sacrifices not many families willingly make. Without their openness and enthusiasm to relocate our lives, I would not have had the opportunity to complete this research, and hopefully, make a difference to others less fortunate than ourselves.

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NOMENCLATURE

ACA	Patient Protection and Affordable Care Act of 2010
ACSC	Ambulatory Care Sensitive Conditions
ADL	Activities of Daily Living
AHRQ	Agency for Healthcare Research and Quality
APR-DRG	All Patient Refined Diagnosis Related Groups
BCBSTX	Blue Cross/ Blue Shield of Texas
CAUTI	Catheter Associated Urinary Tract Infection
CDC	Centers for Disease Control and Prevention
CDI	*Clostridium difficile* Infection
CLABSI	Central-Line Associated Bloodstream Infection
CMS	Centers for Medicare and Medicaid Services
DSHS	Texas Department of State Health Services
FFS	Fee For Service
FPL	Federal Poverty Level
HAI	Healthcare-Associated Infection
HHS	Department of Health and Human Services
ICD-9-CM	International Classification of Diseases, Ninth Revision, Clinical Modification
IOM	Institute of Medicine
MCO	Managed Care Organization
MS-DRG	Medicare Severity Diagnosis Related Groups

NHSN	National Health Safety Network
NQF	National Quality Forum
PDI	Pediatric Quality Indicators
PPH	Potentially Preventable Hospitalization
PPO	Preferred Provider Organization
PQI	Prevention Quality Indicators
PSI	Patient Safety Indicators
SSI	Surgical Site Infection
TANF	Temporary Aid to Need Family
THCIC	Texas Health Care Information Collection
TxHSN	Texas Health Safety Network
VAP	Ventilator Associated Pneumonia

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CHAPTER I

INTRODUCTION

When barriers in access to quality primary care exist, especially for ambulatory care sensitive conditions (ACSC), potentially preventable hospitalizations (PPH) can occur (Agency for Healthcare Research and Quality, 2007; Basu, Friedman, & Burstin, 2002; Bindman et al., 1995). During 2010, in 44 states more than 3.5 million hospital admissions were identified as potentially preventable, translating to a PPH rate of 1,493 per 100,000 individuals (Batelle, 2013). In addition to potentially misallocated resources associated with PPH, any hospital admission carries with it the risk of acquiring a healthcare associated infection (HAI). It is estimated that one in twenty hospital patients will acquire an HAI, translating to an increased risk of death and direct medical costs that were estimated nationwide at $9.8 billion annually in 2012 dollars (Centers for Disease Control and Prevention, National Center for Emerging and Zoonotic Infectious Diseases, & Division of Healthcare Quality Promotion, 2010; Klevens et al., 2007; Scott II, 2009). While both PPH-related access issues and HAI-related quality issues have been studied, there is little in the literature that examines the patient population that is admitted for a PPH and acquires an HAI during the same hospital stay. This gap in our knowledge is the focus of the literature review and analyses in the coming pages.

Individuals admitted to a hospital with a PPH are often thought to have a limited ability to pay for care but nonetheless are driven to seek care due to severity of illness (Bindman et al., 1995). For individuals already limited in their ability to pay for care, the additional costs both physically and financially of an HAI add to the insurmountable

issues related to poverty. It follows that the Patient Protection and Affordable Care Act of 2010 (ACA), as it is implemented, is likely to increase access to preventive healthcare services through increased insurance coverage for preventive healthcare services, which should translate to reductions in PPH. The reduction of PPH in turn should translate to reduced exposure to and incidence of HAIs. However, the impact of ACA on the rate of PPH and HAI is likely to vary across states, due to differences across states in the pre-ACA proportion of the state population without health insurance, coupled with the decision by some states to not expand state Medicaid coverage, as encouraged by the ACA (The Henry J. Kaiser Foundation, 2013).

This anticipated chain of circumstances leads to a central question addressed by this dissertation: Following the full implementation of ACA, will the increase in preventive care cost attributable to improved insurance coverage for individuals with ACSCs be offset by reductions in costs associated a reduced rate of HAI during a PPH? To better characterize the population of people that acquire an HAI during a PPH, Figure 1 illustrates the overlap between the ACSC, PPH, and HAI populations (Figure 1). The shaded region represents the population of people who acquire an HAI during a PPH, and this population is the focus of the following analyses.

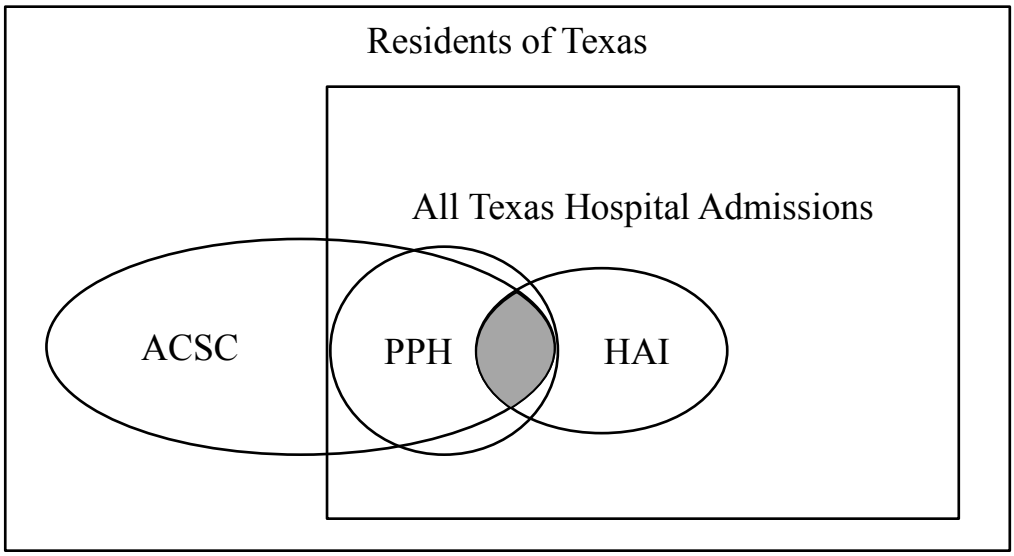


Figure 1. Relationships between the ACSC, PPH, and HAI populations.

The primary focus of ACA is to reduce the proportion of the population without health insurance, which in turn will improve access to care, including preventive services. Accordingly, I have elected to analyze the PPH with HAI population through an access lens (Ansell & Schiff, 1987; Hall, Harman, & Zhang, 2008; Kaiser Commission on Medicaid and the Uninsured, 2011; Vigdor, 2003). The access perspective is appropriate at this time for two reasons. First, the goal of the ACA is to enable or improve access to healthcare by creating options for the uninsured or underinsured to secure affordable health insurance. The ACA strives to accomplish its goal by focusing legislation on insurance market reform and mandates individuals to secure health insurance (Patient protection and affordable care act, 2010). Second, third-party payers influence the provision of healthcare through payment incentives linked to outcomes. For example, Medicare uses its market share power to dictate non-payment to

providers for unacceptable outcomes such as nosocomial hospital events that are deemed preventable (Lee et al., 2012). While payment incentives such as Medicare's non-payment policy should create positive externalities for patients with other insurance, it is important to tease out differences by payer.

Since little has been reported about the PPH with HAI population, I elected to limit the analyses to the state of Texas for two reasons. First, while Texas was not alone when it declined to expand Medicaid under the provisions of the ACA, the administrative implementation of Medicaid does differ from state to state (The Henry J. Kaiser Foundation, 2013). To create a baseline understanding, I determined that using a single state would eliminate the need to account for variation associated with state-based cultural normative values related to healthcare and Medicaid administrative implementation differences between states. Second, Texas has the highest percentage of uninsured at 24%, accounting for 6.1 million individuals in the state of Texas or 12.6% of the nations' uninsured (Kaiser State Health Facts, 2012). As such, it provides researchers with a rich source of information regarding the uninsured.

With the analytic focus of access and study population limited to the state of Texas, the analyses will provide several significant contributions to our base of knowledge. First, the study establishes a method and a baseline measurement in the prevalence and cost of PPH with HAI. The baseline estimation includes a comparison of demographic and payer characteristics between the population at risk and other hospital patients. Further, the baseline cost estimates include an adjusted incremental cost analyses to understand the effect of HAI on the PPH population. Finally, the baseline

metrics will allow for comparisons of prevalence and costs between states and after full implementation of the ACA.

Second is the development of a method for identifying HAIs and HAIs associated with PPH from administrative data. While identification of HAI through administrative discharge data alone is not recommended for surveillance purposes, a method that closely approximates more exact surveillance estimates will provide researchers and policy makers with the ability to estimate costs without increasing reporting burden. Further, with payment linked to nosocomial events, coding and billing methodologies should evolve. The anticipated evolutions in coding would then make the use of administrative data more feasible and reliable especially for the purposes of policy and cost estimates.

This dissertation consists of seven chapters, including this introductory chapter (Chapter I). Chapters II and III will review the existing literature and outline the theoretic basis of the evaluation. The topics in Chapter II provide a brief overview of the ACA, categories of insurance status relevant to this evaluation, a consolidated review of ACSCs and PPH, associations with insurance status, the effects each has on access to quality preventive healthcare, types of HAI found in hospital settings, and established metrics and benchmarks for PPH and HAI. Chapter III describes the evolution of the conceptual model used as the basis of the analytic framework including relevant theory for the behavior of vulnerable populations in their acquisition of healthcare. Chapter IV describes the methodological and analytic approach used to address the research goals of the dissertation, while Chapter V provides a summary of findings from the data analysis.

Chapters VI and VII provide a discussion of the results, the potential implications on future research and policy, and summarizes the key findings and conclusions.

CHAPTER II

LITERATURE REVIEW

Insurance

In a series of reports by the Institute of Medicine (IOM), the IOM highlighted several associations between insurance status and health status. These included insurance status associated with better care and access across preventive, chronic, and acute health services, improved health outcomes, and individuals with continuous health insurance coverage lived longer with a lower rate of decline in health status over the years of life (Institute of Medicine, 2003, p. 13). Also identified in the IOM reports, were associations between uninsurance and forgone health care due to financial and access barriers. According to the IOM reports, forgone healthcare resulted in approximately 18,000 avoidable deaths per year for uninsured adults (Institute of Medicine, 2003, p. 13).

In 2009, the Council of Economic Advisors to President Obama presented an economic justification for market reform of healthcare (Council of Economic Advisors, 2009). The analysis identified slowing growth of healthcare costs through expansion of health insurance coverage as the keys to market reform (Council of Economic Advisors, 2009). Since health insurance has been associated with cost containment, access, and health status, the following review of health insurance briefly describes the ACA and the major types of third party payers that influence the provision of healthcare, including the uninsured.

Patient Protection and Affordable Care Act of 2010

The Patient Protection and Affordable Care Act (ACA) passed in 2010 included provisions intended to improve access to healthcare through disallowing insurers to refuse insurance coverage to individuals with pre-existing conditions, allowing families to continue covering children until age 26, and by providing mechanisms for the uninsured to obtain health insurance (Patient protection and affordable care act, 2010). Since having health insurance has been linked to better health and quality of life, availability of health insurance options potentially addresses societal inequities in access to healthcare (Streeter et al., 2011; Vigdor, 2003).

In an effort to meet its intended goals of cost containment and improved access to healthcare, the ACA, a large and complex piece of legislation, includes provisions such as an individual health insurance mandate, creation of health insurance marketplaces, individually and employer based subsidies to support premium payments, and the expansion of state Medicaid programs(Patient protection and affordable care act, 2010). To finance the provisions in the ACA, the legislation included a variety of fees and penalties intended to underwrite, at least in part, the financial burden created by the law. Some mechanisms include:

- Penalties phased in from 2014 to 2016 for individuals not in compliance with the health insurance mandate (in 2016, $695 per year or 2.5% of household income)
- Penalties on large employers (50 or more full-time employees) with employees utilizing premium tax credits
- Fees on the insurance industry

- Increased Medicare Part A tax rate
- Increase tax on non-qualified expenditures from health savings accounts
- Limit contributions to $2,500 for flexible health spending accounts
- On federal tax returns, increased itemized deductions threshold for non-reimbursed healthcare expenses
- Excise tax on insurers with "Cadillac" health plan premiums

(Kaiser Commission on Medicaid and the Uninsured & Healthcare Marketplace Project, 2011; Patient Protection and Affordable Care Act, 2014).

The ACA facilitates federal financing for the coverage of all individuals not previously eligible for Medicaid and living at or below 133% of the FPL. Starting in 2014, the federal government intends to fund 100% of states' expanded Medicaid population until 2016. Between 2017 and 2019, the federal funding rate is legislated to decline from 95% to 93% of the cost of the expanded Medicaid population. For 2020 and beyond, the ACA is legislated to fund 90% of the Medicaid expansion population (Kaiser Commission on Medicaid and the Uninsured & Healthcare Marketplace Project, 2011). Additionally, the ACA legislates that the federal government will finance increased payments to providers so that Medicaid payment rates are equivalent to Medicare payment rates (Kaiser Commission on Medicaid and the Uninsured & Healthcare Marketplace Project, 2011). Despite the significant financial incentives by the federal government to pay for new beneficiaries under the Medicaid expansion, it is estimated that states will incur a 17.8% increase in payments to hospitals for care associated with the Medicaid expansion between 2013 and 2022 (Holahan, Buettgens,

Carroll, & Dorn, 2012). In Texas, the estimate is higher at 22.2% increase in payments to hospitals during the same time frame (Holahan et al., 2012).

Another facet of the ACA establishes health insurance exchanges or health insurance marketplaces for individuals who do not qualify for Medicaid or Medicare and are not covered by employer-sponsored health insurance. Currently, individuals in households with income between 134- 400% of the FPL should have access to premium tax credits and cost-sharing subsidies to lower the cost of health insurance. Qualified health plans are required to include health benefits defined as "essential," including ambulatory patient services, emergency care, hospitalization, obstetric, newborn, pediatric care, mental health services, prescription drug coverage, laboratory services, rehabilitation services, and preventive services that include chronic disease management services (42 U.S.C. §18022).

Although the Supreme Court ruling validated the constitutionality of the individual health insurance mandate in July 2012, the Supreme Court also determined that the legislation could not force states to expand their Medicaid programs in order to continue receiving existing funds (Roberts, 2012). Given the choice to expand, to date, Texas along with 18 other states have declined to expand Medicaid under the terms outlined by the ACA (Perry, 2012; The Henry J. Kaiser Foundation, 2013). Texas was also among 27 states that opted to participate in the federal health insurance exchange (The Henry J. Kaiser Foundation, 2013).

Accordingly, eligible Texans should have access to health insurance through a federal health insurance exchange. However, the implementation of the ACA met with

substantial political resistance and roll-out issues resulting in delays of some portions of the law, and difficulties in opening the federal insurance exchange for individuals to the public (Burgess, 2013; Hu, 2013; Morelli, 2013). At the end of the rollout period, states enrolled 25.4% of the estimated federal exchange eligible population (Kaiser Family Foundation, 2014). State-base exchanges appeared to have more success in signing up exchange eligible individuals at 29.5% of the exchange eligible population, while the state of Texas was just below the national average with 23.3% of the 3.1 million Texans estimated to be eligible to participate in the exchange (Kaiser Family Foundation, 2014).

Medicare and the Medicare population

Entitlement legislation passed in 1965 established the federally based insurance program we know as Medicare (42 U.S.C, chapter 7 subchapter XVIII). The insurance program covers individuals 65 years of age and over, individuals with certain disabilities, and individuals with end-stage renal disease (Centers for Medicare and Medicaid Services, 2013a). The program includes hospital insurance, medical insurance, and prescription drug coverage and accounted for 28.4% of the health insurance market in 2012 or $572.5 billion (Centers for Medicare and Medicaid Services, 2013a; Centers for Medicare and Medicaid Services, 2014)

While private health insurance accounts for nearly half of the health insurance market, it is estimated that Medicare beneficiaries accounted for 47% of inpatient costs nationally in 2011 (Centers for Medicare and Medicaid Services, 2014; Torio & Andrews, 2013). As the largest consumer of inpatient services nationally, the Medicare program has moved from being a passive payer to a more active consumer of healthcare,

working to incent quality cost-effective healthcare for its beneficiaries through payment structures and payment incentive programs. Payment structures include the prospective payment system, fee-for-service, and capitated Medicare known as Medicare Advantage (Averill et al., 1998; Averill, Goldfield, Muldoon, Steinbeck, & Grant, 2002; Averill et al., 2009). Incentives pay providers for evidence-based quality care or penalize providers through reduced payments by using programs such as pay for performance, pay for reporting, and value-based purchasing (Centers for Medicare and Medicaid Services, 2009; CMS Hospital Pay-for-Performance Workgroup, 2007; Maio, Goldfarb, Carter, & Nash, 2003). As cost of healthcare has escalated, the Medicare program has used its purchasing power in the healthcare marketplace to implement and revise incentive programs intended to contain rising costs and improve outcomes for its beneficiaries.

Medicaid and the Medicaid population

Established through federal legislation in 1966, Medicaid is a state run federal/state matching funds program designed to help ensure access to healthcare for the poor and impoverished (42 U.S.C., chapter 7 subchapter XIX). Currently, Medicaid in Texas covers the federally mandated populations including: (a) the categorically needy as defined by participation in Temporary Aid to Needy Families (TANF); (b) pregnant women and children up to six years with a family income up to 133% of the federal poverty level (FPL); (c) children six to 19 years with family income under 100% of the FPL; (d) parents of qualified children living at or below 42% of the FPL; and (e) the aged, blind and disabled living at or below 74% of the FPL (Rowland, 2005).

Under Medicaid legislation, Texas opted to expand the population covered to include: (a) family members of qualified TANF recipients with incomes up to 14% of the FPL; (b) individuals denied TANF funds because of extended family resources with incomes up to 185% of the FPL; (c) pregnant women who would otherwise be eligible to receive TANF funds with incomes up to 185% of the FPL; (d) pregnant women through their postpartum period who may have otherwise lost funding due to an increase in family income; (e) the aged, blind and disabled receiving cash assistance through Supplemental Security Income (SSI) funds with incomes up to 74% of the FPL; (f) individuals denied SSI funds due to changes in definitions of disability with incomes up to 74% of the FPL; (g) institutionalized individuals who meet state Medicaid eligibility criteria with incomes up to approximately 220% of the FPL; (h) Medicare beneficiaries with income that does not exceed 100% of the FPL; (i) individuals eligible for buy-in participation through the BBA Work Incentive Group with incomes up to 250% of the FPL; and (j) individuals eligible for buy-in participation through the Family Opportunity Act with incomes up to 300% of the FPL (State of Texas, 1980; Tavenner, 2011; Texas Health and Human Services Commission, 2008; Texas Health and Human Services Commission, 2012a; Texas Health and Human Services Commission, 2012b; Texas Health and Human Services Commission, 2012c; Texas Health and Human Services Commission,).

Medicaid was distributed to Texans through four programs including traditional Medicaid using a fee-for-service payment structure, Children's Health Insurance Program (CHIP), State of Texas Access Reform (STAR) and STAR+PLUS using a fully

capitated managed care payment structure, and the Women's Health Program(Texas Health and Human Services Commission, 2008; Texas Health and Human Services Commission, 2012b; Texas Health and Human Services Commission, 2012c; Texas Health and Human Services Commission,). Additionally, Texas has created the Health Insurance Premium Payment (HIPP) program and the Medical Transportation Program to aid the impoverished in Texas (Texas Health and Human Services Commission, ; Texas Health and Human Services Commission,). To qualify for these programs, individuals must be U.S. citizens or a qualified legal permanent resident, and a Texas resident. Other qualifications relate to the specific population served by the program. For all programs, qualifying income level changes with the number of family members to allow more money to stay with larger families. Qualifying income levels were assigned using the FPL. For 2012, the FPL for a family of four was $23,050 (U.S. Department of Health & Human Services, 2012).

There are two additional topics relevant when discussing the Medicaid eligible population in Texas. First, Texas has moved to phase out or significantly reduce fee-for-service payment in the Medicaid population (Wool, 2012). Until March 2012, STAR and STAR+PLUS were available primarily in urban areas. In March 2012, the state transitioned the majority of qualified beneficiaries from traditional Medicaid FFS to the STAR capitated payment structure with STAR+PLUS expanding statewide in 2014 (Wool, 2012). The transition primarily affected Medicaid beneficiaries in rural settings. Texas also removed state level Upper Payment Limit funding mechanisms from its

Medicaid program to allow those funds to be used more effectively in managed care (McKethan & Menges, 2006; State of Texas, 1980; Wool, 2012).

Second, national Medicaid participation rates identified were below 80% of the number of eligible individuals (Weil, 2003). By eligibility category, participation rates were 72% of eligible children, 51% of eligible non-elderly adults, 78% of qualified Medicare beneficiaries, and 16% of the eligible specified low-income Medicare beneficiaries (Weil, 2003). A more recent examination of participation compared different definitions and estimates. Estimates for adults nationally ranged from 32.3% to 81.3%, and child participation rates were 57.0% to 96.1% (Sommers et al., 2012).

Uninsurance and the uninsured population

Nationally, more than 48.6 million individuals were uninsured in 2011 (Kaiser State Health Facts, 2012). While the state of Texas accounted for only 8.2% of the national population, it accounted for 6.1 million or 12.6% of the nations' uninsured and had the highest state uninsurance rate of 24% (Kaiser State Health Facts, 2012). Only California had more uninsured individuals, approximately 7.3 million individuals or 20% of California's population. Behind Texas with 3.8 million uninsured individuals was Florida (Kaiser State Health Facts, 2012). Together California, Texas, and Florida accounted for more than a third of the uninsured population in the United States.

When the uninsured in Texas were examined by demographic and economic characteristics, more than half of the 6.1 million individuals were male and approximately 80% were adults. When examined by race, 59% were Hispanic. Additionally, 69% of the Texas uninsured lived in households with at least one full-time

worker. And even though most households had at least one worker, total income for 52% fell at or below 138% of the FPL (Kaiser State Health Facts, 2012). It is unclear from the literature, how many of the working uninsured are eligible and not enrolled in insurance programs such as Medicaid. But, we do know that approximately 3.6 million individuals were enrolled in the Texas Medicaid program in 2011, and of the uninsured population in Texas in 2011, an estimated 782 thousand were eligible but not enrolled in Medicaid (Texas Department of State Health Services, 2013a; Texas Health and Human Services Commission, 2013). While the rate of uninsured by gender and age are similar to the United States' rates, the proportion of the Texas population that is uninsured is consistently higher in all other economic categories compared to the United States average with the exception of full dual eligibles and the disabled population (Kaiser State Health Facts, 2012).

In border states such as Texas, the uninsured population includes undocumented immigrants and their use of healthcare. Although undocumented immigrants utilize less healthcare than their citizen counterparts, the immigrant population both legal and illegal account for approximately 22% of the uninsured (Hoffman, Schwartz, Tolbert, Cook, & Williams, 2007; Lorden, 2008). Representative Michael C. Burgess (R-Texas) cited the large numbers of immigrants in Texas as a primary reason Medicaid expansion would not address all of the relevant issues in Texas especially concerning reductions in Disproportionate Share Hospital (DSH) funds through the ACA guided expansion of Medicaid (E. Smith, 2012).

Potentially preventable hospitalizations

Definition of and existing metrics for PPH

ACSC are defined as chronic health conditions that if managed with timely primary care, hospitalization could be avoided (J. Billings et al., 1993). Hospitalizations that result from untreated or under-treated ACSC are commonly known as PPH (Basu, Friedman, & Burstin, 2006; Bindman et al., 1995; Bindman, Chattopadhyay, Osmond, Huen, & Bacchetti, 2005; Oster & Bindman, 2003). PPH accounted for 3.9 million hospitalizations and an estimated $31.9 billion in total hospital costs in 2010 (Torio, Elixhauser, & Andrews, 2013).

Initially, six expert physicians defined PPH by performing a medical chart review and identifying the ICD-9-CM codes thought to reflect hospital utilization by the indigent and other individuals with healthcare access barriers (J. Billings et al., 1993; Friedman & Basu, 2004). The identification of PPH has evolved, and can be identified through 13 adult and 5 pediatric measures using the Prevention Quality Indicators (PQI) and Pediatric Quality Indicators (PDI). The Quality Indicators were developed by the Agency for Healthcare Research and Quality (AHRQ) Evidence-based Practice center, the University of California San Francisco, and Stanford University (Agency for Healthcare Research and Quality, 2007; Agency for Healthcare Research and Quality, 2008; Friedman & Basu, 2004).

Developed through comprehensive literature review and validation testing, the 14 PQI and 4 PDI use inpatient administrative discharge data including ICD-9-CM diagnoses codes, Medicare Severity-Diagnosis Related Groups (MS-DRGs), and All-

Patient Refined Diagnosis Related Groups (APR-DRGs) with associated severity measures to identify inpatients with hospitalizations where an ACSC is the principal reason for admission (Agency for Healthcare Research and Quality, 2013c; Batelle, 2013). The 13 adult and 5 pediatric Quality Indicators reflecting PPH include diabetes short-term complications, perforated appendix both adult and pediatric, pediatric diabetes, diabetes long-term admissions, chronic obstructive pulmonary disease, hypertension, congestive heart failure, low birth weight, dehydration, pediatric gastroenteritis, bacterial pneumonia, urinary tract infection both adult and pediatric, angina without procedure, uncontrolled diabetes, asthma both adult and pediatric, and lower-extremity amputation among diabetes patients (Agency for Healthcare Research and Quality, 2013b). Since development and refinement, ten of the PQIs are endorsed by the National Quality Forum as validated and nationally recognized measures of quality and access to healthcare (National Quality Forum, 2013b).

PPH as a reflection of access to healthcare and the role of insurance status

ACSC and the PPH associated with them are two indicators known to reflect access to primary care (J. Billings et al., 1993; J. Billings & Anderson, 1996; Bindman et al., 1995; Friedman & Basu, 2004; Ricketts, Randolph, Howard, Pathman, & Carey, 2001; Saha, Solotaroff, Oster, & Bindman, 2007; Shi, Samuels, Pease, Bailey, & Corley, 1999). The evolution of using the PQI to understand preventive healthcare access through ACSC related PPH began when early studies explored PPH to understand underlying determinants of access. In an early study of ACSCs and PPH by Billings et al. (1993), hospital admissions were blocked into three categories: Conditions where

primary care had a limited ability to prevent the admission, ACSC where primary care may have prevented the admission, and referral sensitive procedures reflecting surgery that was potentially the result of barriers to access or specialty care. The study found determinants of access were income, race, and age, with the low-income black population in the age range of 25-44 years most affected. (J. Billings et al., 1993).

In 1996, Bindman et al. examined five ACSC that resulted in PPH for 250 ZIP codes in San Francisco, California. Validating PPH as a measure of access, Bindman et al., (1996), like Billings et al., (1993), found race and income predicted PPH. Through a regression analysis, an inverse relationship between insurance status and PPH was attributed to inferior access to healthcare among the uninsured. (Bindman et al., 1995). The subsequent focus to reduce PPH through insurance related access to preventive care has been associated with a decrease of PPH by 6.2 percent from 2005 to 2010 in the United States (Ayanian, Weissman, Schneider, Ginsburg, & Zaslavsky, 2000; Bharmal & Thomas, 2005; Hadley & Cunningham, 2004; Kaiser Commission on Medicaid and the Uninsured, 2011; Torio et al., 2013; Vigdor, 2003).

Effects of payment structure

Since identifying an association between insurance status and PPH, evidence suggests insurance structured through managed care payment models do better than fee-for-service payment structures to reduce PPH (Backus, Moron, Bacchetti, Baker, & Bindman, 2002; Basu, Friedman, & Burstin, 2002; Basu, Friedman, & Burstin, 2004; Basu et al., 2006; Basu, Thumula, & Mobley, 2012; Bindman et al., 2005; Bindman, Chattopadhyay, & Auerback, 2008a; Bindman, Chattopadhyay, & Auerback, 2008b;

Laditka & Laditka, 2001). When examining vulnerable populations, at least two studies substantiated where vulnerable populations were part of managed care programs significant decreases in PPH resulted (Backus et al., 2002; Zeng et al., 2006). For the elderly, Medicare Advantage, the Medicare managed care program, did not demonstrate reduced hospitalizations in one recent study (Baicker, Chernew, & Robbins, 2013). However, in markets with increased Medicare Advantage penetration, spillover effects included younger populations experiencing lower hospitalization costs and shorter lengths of stay (Baicker et al., 2013). Additionally, reduced expenditures offset the higher payment rates for Medicare Advantage patients (Baicker et al., 2013).

In another recent study of Medicare Advantage, the effects of payment structure and selection bias on hospital admissions were examined. A differentiating characteristic was whether or not the market was in a county within a Metropolitan Statistical Area (MSA) where the county population was above or below 250,000 individuals (Afendulis, Chernew, & Kessler, 2013). In counties above the 250,000 threshold, increased payment levels facilitated providers in offering more services while simultaneously encouraging greater market penetration. The payment incentive produced reductions in hospitalizations including those associated with ACSC in the MSA counties with populations over 250,000 (Afendulis et al., 2013).

In rural and underserved areas, the presence of a Rural Health Clinic or a Federally Qualified Health Clinic was associated with reductions in PPH compared to underserved communities with no public clinics (Epstein, 2001; Falik, Needleman, Wells, & Korb, 2001; Zhang, Mueller, Chen, & Conway, 2006). Since Rural Health

Clinics and Federally Qualified Health Clinics are federally supported preventive care in underserved communities, and exist in both managed care and fee-for-service markets, it is unclear whether the effects are related to payment structure.

Effects of Medicare on PPH

For the elderly, the primary insurance provider is Medicare with the poor elderly also covered by Medicaid. Individuals covered by both Medicare and Medicaid are known as dual eligibles. Nationally, two-thirds of dual eligibles fully qualify for both programs with the remaining portion qualifying for assistance with Medicare premium and cost sharing payments (Clemans-Cope & Waidmann, 2011). While dual eligibles accounted for about a sixth of each population, they simultaneously accounted for 40% of each programs' spending estimated to exceed $315 billion in 2011 (Clemans-Cope & Waidmann, 2011).

In 1998, individuals with Medicare as their only insurer had fewer PPH compared to other Medicare beneficiaries with Medicaid or private insurance as part of their insurance coverage (Culler, Parchman, & Przybylski, 1998). Other factors for the Medicare population identified with increased odds of a PPH included increased age, black, less than college education, reduced health status, diabetes, coronary heart disease, two or more ADLs, and living in either a core metropolitan statistical area or a rural county (Culler et al., 1998). When diabetic Medicare beneficiaries' claims data were analyzed for PPH, comorbid conditions, especially heart failure related comorbidities, were associated with an increased odds of a PPH (Niefeld et al., 2003).

A more recent study of PPH for the Medicare population measured the relationship between PPH and continuity of care measures (Nyweide et al., 2013). The results demonstrated improved continuity of care was inversely related to PPH when adjusted for demographics, Medicare only verses dual-eligibility, and comorbidities as measured through CMS hierarchal condition categories score (Nyweide et al., 2013). While the hazard ratio by insurance status for Medicare verses dual-eligibles was significant, where Medicare only were less likely to have a PPH, the reported hazard ratio was 1.06 (Nyweide et al., 2013). Other research suggested that lower rates of PPH for individuals 65 years of age and older may be due to participation in Medicare (Laditka & Laditka, 1999).

Effects of Medicaid on PPH

Although access to preventive healthcare has improved for low-income populations through expansions of Medicaid and the introduction of the State Children's Health Insurance Program (SCHIP), it does not completely equalize access to healthcare due to limits associated with economic status, rurality, or market availability of services. For example, interruptions in Medicaid coverage were associated with higher rates of PPH for certain conditions (Bindman, Chattopadhyay, & Auerback, 2008a). While consistently higher rates of ACSC and PPH are associated with low-income, non-white, urban populations (J. Billings et al., 1993; J. Billings & Anderson, 1996; Bindman et al., 1995; DeLia, 2003; Friedman & Basu, 2004; Oster & Bindman, 2003; Shi et al., 1999).

Counter to expectations, in 2007 a study examining expansion of Medicaid in Oregon found an increase in PPH for Medicaid patients (Saha et al., 2007). Another

more recent study of the 2008 Medicaid expansion by lottery in Oregon, allowed for the examination of Medicaid insurance status on clinical outcomes (Baicker et al., 2013). While utilization of preventive services, including the detection and management of diabetes increased, two-year results found little evidence of improved outcomes (Baicker et al., 2013). The study did find lower rates of depression and near elimination of personal catastrophic healthcare-related financial events for Medicaid participants as compared to the eligible but not selected by lottery in the Oregon Medicaid expansion (Baicker et al., 2013).

Healthcare-associated infections

Healthcare-associated infections (HAI) are defined as an infection that was not present or incubating at the time of admission to a healthcare setting (Center for Disease Control and Prevention & National Healthcare Safety Network, 2013; Centers for Disease Control and Prevention, National Center for Emerging and Zoonotic Infectious Diseases, & Division of Healthcare Quality Promotion, 2010; Horan, Andrus, & Dudeck, 2008; Sydnor & Perl, 2011). Infections transmitted by healthcare providers were first identified in 1847 by Ignaz Semmelweis (Dixon, R.E, 2011; Sydnor & Perl, 2011). Since that time to the outbreak of nosocomial penicillin-resistant staphylococcal in the 1950s, improvements in the hospital setting focused on creating and maintaining a sanitary environment (Dixon, R.E., 2011; P. W. Smith, Watkins, & Hewlett, 2012; Sydnor & Perl, 2011). However, with the emergence of drug-resistant pathogens and subsequent increases in HAIs, the need for more rigor in tracking HAI became apparent (Hughes, 1987; P. W. Smith et al., 2012; Sydnor & Perl, 2011).

In response to emerging drug-resistant pathogens and the need for more rigorous methods to contain them, the CDC took several steps to address HAI. One of the first was to establish the National Nosocomial Infections Surveillance (NNIS) system (Hughes, 1987). Eventually incorporated into the National Health Safety Network (NHSN) with the National Surveillance System for Healthcare workers and the Dialysis Surveillance Network in 2005, NHSN is an electronically-based HAI tracking system (Centers for Disease Control and Prevention, 2011; Centers for Disease Control and Prevention, 2013). Functions of NHSN include collecting data, providing support, measuring progress, and providing information to providers, states and regions regarding status of infection prevention (Centers for Disease Control and Prevention, 2011; Centers for Disease Control and Prevention, 2013).

While NHSN started as a voluntary reporting system to track HAI, 32 states now mandate reporting to NHSN including Texas (Center for Disease Control and Prevention, 2013; Texas Department of State Health Services, 2013b). Additionally, the Centers for Medicare and Medicaid Services (CMS) require HAI reporting to NSHN for hospitals participating in the Hospital Inpatient Quality Reporting (IQR) program (Malpiedi et al., 2013; Vinyard, 2013). Using a phased-in approach, mandated data collection began in late 2011 to be complete in 2013 for selected HAI (Malpiedi et al., 2013; Texas Department of State Health Services, 2013b).

The CDC also developed and implemented the Study on the Efficacy of Nosocomial Infection Control (SENIC) (Haley, Quade, Freeman, & Bennett, 1980; Hughes, 1987; Sydnor & Perl, 2011). A ten-year study that measured the effectiveness

of infection control programs found the following four elements necessary for a successful infection control program:

1. Feedback to staff regarding surveillance rates
2. Adherence to infection prevention practices
3. Presence of Infection Prevention Specialist to supervise collection and dissemination of surveillance information
4. Presence of a physician or microbiologist specially trained for infection prevention

(Hughes, 1987; Sydnor & Perl, 2011)

Today, the CDC tracks numerous HAI pathogens with the majority traced to one or more of five types of HAI: Surgical Site Infections (SSI), Central Line-Associated Blood Stream Infection (CLABSI), Catheter-Associated Urinary Tract Infection (CAUTI), Ventilator Associated Pneumonia (VAP), and Clostridium difficile Infection (CDI) (Centers for Disease Control and Prevention, National Center for Emerging and Zoonotic Infectious Diseases, & Division of Healthcare Quality Promotion, 2012; Centers for Disease Control and Prevention, National Center for Emerging and Zoonotic Infectious Diseases, & Division of Healthcare Quality Promotion, 2013). Described below, these five types of HAI affected more than 1.7 million individuals causing nearly 99,000 deaths in 2002 with more recent cost estimates ranging from $9.8 billion to $45 billion annually (Klevens et al., 2007; Scott II, 2009; Zimlichman et al., 2013).

Also included in the description of each HAI type is a listing of Health and Human Services (HHS) and National Quality Forum (NQF) recognized measures. The

National Quality Forum (NQF) endorses public use healthcare measures through expert committees that include various stakeholders including patients. Considered the gold standard, measures endorsed by the NQF reflect relevant measurement of identified healthcare issues and are used in payment and public reporting strategies (National Quality Forum, 2013c). While HHS measures are used in the same way, not all are endorsed by the NQF.

Surgical site infections (SSI)

An SSI is an infection that occurs in or around the area where a surgery was performed, develops within 30 to 90 days of surgery, and is categorized as superficial, deep tissue, or organ space in nature (Center for Disease Control and Prevention & National Healthcare Safety Network, 2013). For SSI, HHS uses three outcome measures (Department of Health and Human Services, 2013). The first uses NHSN data to target specific types of surgery including colon surgery and abdominal hysterectomies. Used by CMS in its pay-for-reporting initiative, the NQF endorsed measure reported on the Hospital Compare website for inpatient quality reporting (Department of Health and Human Services, 2013; National Quality Forum, 2013a). The second SSI measure is an observed over expected ratio also using NHSN data. Only ratios for surgical sites specified in the Surgical Care Improvement Project (SCIP) are calculated for this NQF endorsed measure (Department of Health and Human Services, 2013; National Quality Forum, 2013a). The final measure is Patient Safety Indicator 13 – Postoperative Sepsis rate. Developed by AHRQ for use with inpatient discharge data, this measure reflects the rate of surgeries that discharge with a secondary diagnosis of sepsis where the length of

stay is four days or more (Agency for Healthcare Research and Quality, 2013c; Department of Health and Human Services, 2013). While the last measure is not endorsed by the NQF, it is used in national quality reports such as the National Healthcare Quality Report and the National Healthcare Disparities Report (Department of Health and Human Services, 2013).

Central line-associated blood stream infection (CLABSI)

CLABSI is an infection that manifests in the bloodstream and enters the body through a line inserted into a major vein for the delivery of medication and fluids during an inpatient stay (Center for Disease Control and Prevention, National Center for Emerging and Zoonotic Infectious Diseases, & Division of Healthcare Quality Promotion, 2012b). HHS identified 12 measures to track CLABSI. Four measures developed by AHRQ's Quality Indicator (QI) program are included in the HHS measure inventory. Patient Safety Indicator (PSI) 7 and PSI 23 reflect adult CLABSI rates by provider and geographic area respectively, while Pediatric Quality Indicator (PDI) 12 and Neonate Quality Indicator (NQI 3) reflect CLABSI for children and neonates respectively (Agency for Healthcare Research and Quality, 2008; Batelle, 2013; Department of Health and Human Services, 2013). All four of the AHRQ QI measures are endorsed by the NQF (Department of Health and Human Services, 2013; National Quality Forum, 2013a). Of the remaining eight measures, six use NHSN data, and five of the six are endorsed by the NQF (Department of Health and Human Services, 2013; National Quality Forum, 2013a). The six measures based on NHSN data are used for public reporting, accountability, pay-for-reporting, pay-for performance, quality

reporting, and surveillance. While five of the six NHSN based measure use total central line days in the denominator, the measure used for surveillance is a ratio of observed over expected CLABSI (Department of Health and Human Services, 2013).

Catheter-associated urinary tract infection (CAUTI)

Urinary tract infections are the most common HAI reported, and include infections anywhere in the urinary system (Center for Disease Control and Prevention, National Center for Emerging and Zoonotic Infectious Diseases, & Division of Healthcare Quality Promotion, 2012a; Saint et al., 2006). Fifteen to twenty-five percent of patients receive urinary catheterization during their inpatient stay subjecting them to the risk of a CAUTI (Center for Disease Control and Prevention, National Center for Emerging and Zoonotic Infectious Diseases, & Division of Healthcare Quality Promotion, 2012a; Saint et al., 2006). Increased duration of catheterization is associated with higher risk of a CAUTI (Center for Disease Control and Prevention, National Center for Emerging and Zoonotic Infectious Diseases, & Division of Healthcare Quality Promotion, 2012a; Saint et al., 2006; Wald, Epstein, Radcliff, & Kramer, 2008). Three of the four CAUTI measures used by HHS are endorsed by NQF and use NHSN data (Department of Health and Human Services, 2013; National Quality Forum, 2013a). All three of the NHSN measures are based on an observed over expected method and are used in quality reporting, pay-for-performance, or surveillance. The fourth measure uses claims data for its calculations and is used in pay-for-performance, and public reporting such as Hospital Compare (Department of Health and Human Services, 2013).

Ventilator associated pneumonia (VAP)

Infections of the lung related to ventilator use fall into the VAP type of HAI (Center for Disease Control and Prevention, National Center for Emerging and Zoonotic Infectious Diseases, & Division of Healthcare Quality Promotion, 2012c). Estimated to occur in 8% to 28% patients requiring mechanical ventilation, VAP that occurs after four or more days of mechanical ventilation is more likely to be associated with a drug resistant pathogen (Amin, 2009). With mortality associated with VAP estimated between 24% and 40% , it is interesting that HHS and the NQF do not have any active measures for VAP(Amin, 2009; Department of Health and Human Services, 2013; National Quality Forum, 2013a). While the AHRQ QI program does track pneumonia related death rates (Inpatient Quality Indicator 20), it has not developed a measure to assess whether an HAI related VAP has occurred (Batelle, 2013).

Clostridium difficile infection (CDI)

Unlike the other HAI types tracked by the CDC, CDI is not associated with a mechanical device or invasive procedure. CDI is a diarrhea causing spore-based infection associated with antibiotic use and hospitalization (McDonald et al., 2007; Sunenshine & McDonald, 2006). Nearly 14,000 deaths are associated with CDI each year (Center for Disease Control and Prevention, National Center for Emerging and Zoonotic Infectious Diseases, & Division of Healthcare Quality Promotion, 2013). HHS houses two measures for CDI. The NQF endorsed measure used in pay-for-reporting, Hospital Compare, and the Hospital Inpatient Quality Report follows the NHSN Surveillance Infection Ratio (SIR) where the total number of HAI CDI cases are divided

by either total patient days or admissions for the month observed (Department of Health and Human Services, 2013; National Quality Forum, 2013a). The second HHS measure also used NHSN data and is used as an accountability measure in Quality Improvement Organizations (Department of Health and Human Services, 2013).

Identifying HAI from administrative data

Identification of HAI through the use of administrative data has met with little success (Jhung & Banerjee, 2009; Klevens et al., 2007; Patrick et al., 2013; Sherman et al., 2006; Stevenson et al., 2008; Stone, Horan, Shih, Mooney-Kane, & Larson, 2007). With CLABSI as the exception, a method with the ability to use administrative discharge data to consistently identify other HAIs has had varied results (Jhung & Banerjee, 2009; Sherman et al., 2006; Stevenson et al., 2008; Stone et al., 2007). For CDI, there is only one ICD-9-CM code making it easy to identify from administrative data. However, difficulties arise in determining whether the *Clostridium difficile* pathogen was community-acquired or healthcare-acquired. Indicators now included within the administrative data identify whether a diagnosis was present at the time of admission. The present on admission information should make it possible to achieve better concordance between administrative data and NHSN data.

More difficulties arise for SSI, CAUTI, and VAP. Due to multiple pathogens and settings in which these infections arise, it has been difficult to establish a consensus on which coding schemes are consistent across providers to identify SSI, CAUTI, and VAP. Limitations in identifying HAI from administrative data have been attributed to limited number of diagnosis fields to capture payment information, coders with limited clinical

expertise, and multiple diagnosis fields being required to identify a single condition (Jhung & Banerjee, 2009; Sherman et al., 2006). With 25 diagnosis fields now available, present on admission information, procedure codes, and day of hospital stay a procedure was performed, it may be possible to refine administrative identification methods of HAI to align more accurately with NHSN or TxHSN. Despite mixed results in using administrative data for HAI identification, Jhung et. al, 2009, recommend using as many as possible diagnosis fields, validating against other data sources, using multiple codes for diagnosis and procedures, and report results as a range of estimates (Jhung & Banerjee, 2009).

CHAPTER III

CONCEPTUAL AND THEORETICAL FOUNDATION

Behavioral model of health services utilization

When initially developed in the late 1960's, Andersen's behavioral model of health services utilization used the family as the unit of analysis to predict the use of healthcare (R. M. Andersen, 1995; R. M. Andersen, 2008). The model categorized factors that lead to healthcare utilization as predisposing characteristics, enabling resources, and needs. Predisposing characteristics included demographics, social structure, and health beliefs; enabling resources included ability to pay and were measured at the family or community level; and need was delineated as perceived by the individual or evaluated by a healthcare provider (R. M. Andersen, 1995; R. M. Andersen, 2008). As the theory evolved, the level of analysis moved from family to individual using family characteristics such as income to measure enabling resources.

The purpose of developing the behavioral model was to uncover factors that affect utilization, resulting in a model that ultimately addressed access (R. M. Andersen, 1995; Culler, Parchman, & Przybylski, 1998). In particular, Andersen (1995) articulated and differentiated three key concepts adding a fourth as the model evolved. These include potential verses realized access, equitable verses inequitable access, the concept of mutability, with the role of effective and efficient access coming in later versions of the model (R. M. Andersen, 1995; R. M. Andersen, 2008). While these four concepts are not the only articulated by Andersen's model, they quantify levels of the access construct that are of interest to this study.

For the first concept, access was delineated into two levels including potential access and realized access. Potential access was equated to the presence of enabling resources such as income, health insurance, or proximity to providers, while realized access was equated to the utilization of healthcare. Although enabling resources facilitate realized access, need can drive individuals to access healthcare despite lack of sufficient enabling resources.(R. M. Andersen, 1995; R. M. Andersen, 2008; Ricketts, Randolph, Howard, Pathman, & Carey, 2001)

According to Andersen's behavioral model of healthcare utilization, we can assess whether access is equitable based upon what predicts realized utilization (R. M. Andersen, 1995). Where need or demographics predict realized access, Andersen (1995) defined access as equitable within the population studied. Where health beliefs, social structure, or enabling resources predict realized access, Andersen (1995) defined access as inequitable (R. M. Andersen, 1995; R. M. Andersen, 2008; Gaskin & Hoffman, 2000; Shi & Stevens, 2005).

Third, the concept of mutability addresses how easily the factors that affect access can be changed (R. M. Andersen, 1995; R. M. Andersen, 2008). Of predisposing characteristics, enabling resources and need, enabling resources are identified as the most easily changed or mutable through policy initiatives or economic incentives (R. M. Andersen, 1995). Insurance status and income are examples of enabling resources that have recently been affected by policy and legislation such as the ACA and changes in the minimum wage (Sudano & Baker, 2003).

Finally, with the increased emphasis on outcome measures, the behavioral model evolved in the 1980s and 1990s to account for efficient and effective access to healthcare (R. M. Andersen, 1995; R. M. Andersen, 2008). Where access translates to improved health status, effective access is said to exist, and where gains in health status are consistent or increasing with the amount of healthcare consumed, efficient access is said to exist (R. M. Andersen, 1995; Ricketts et al., 2001; Sudano & Baker, 2003).

Difficulties in adapting the behavioral model to measure access are varied. While variables such as age, race, and gender cannot be changed and are easy to identify as predisposing characteristics, more difficulty arises when assessing other predisposing characteristics such as health beliefs and social structure especially when datasets are not comprehensive at the individual level (R. M. Andersen, 2008; Carrillo et al., 2011). Recognized as both an outcome and determinant of healthcare utilization, health status when used as a proxy for evaluated need can introduce endogeneity as health status is also an outcome measure (Figure 2) (Gelberg, Andersen, & Leake, 2000). Given these considerations, appropriate causal conceptualization of access is imperative when using the behavioral model.

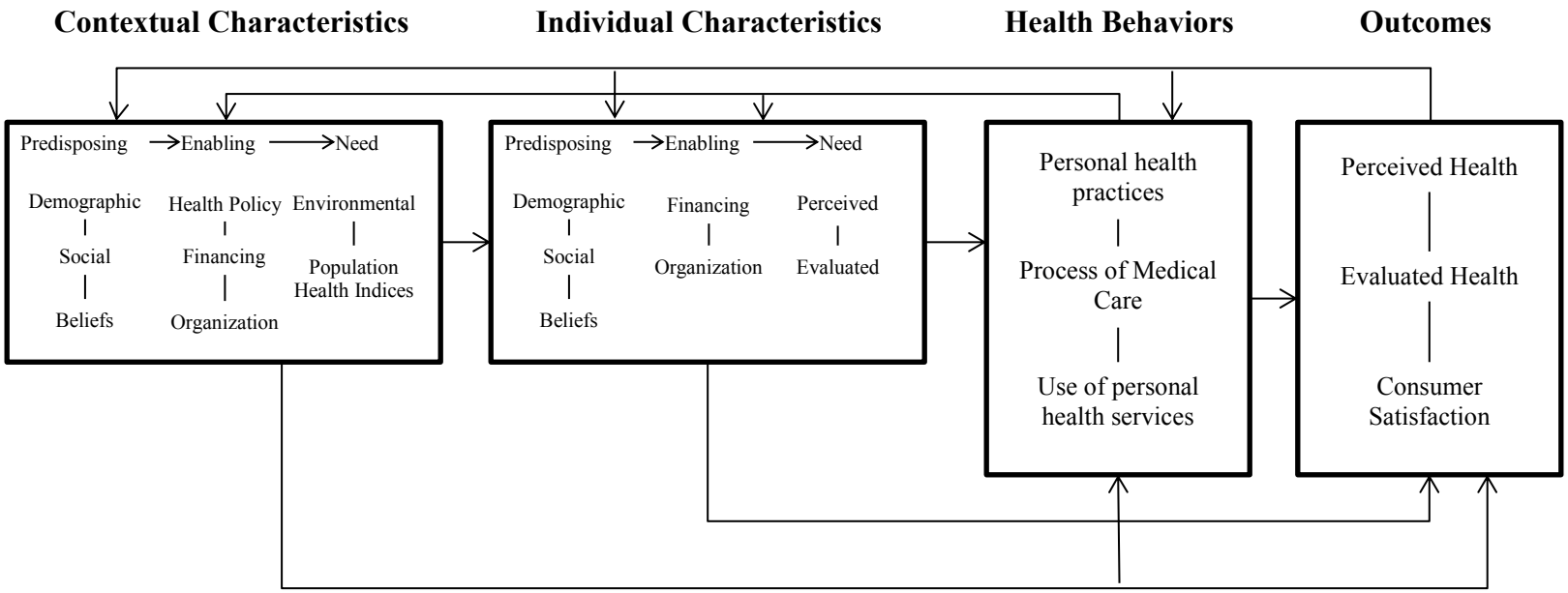
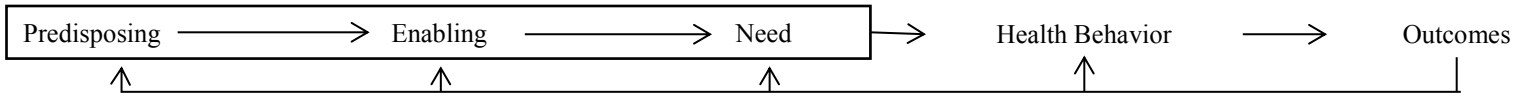


Figure 2. Andersen's behavioral model of healthcare utilization. (Revisited)
Source: Andersen, R.M. *Medical Care* 2008; 46: p.651

Behavioral model for vulnerable populations

Contributors to Andersen's evolving behavioral model for healthcare utilization also created a version specifically for vulnerable populations (Gelberg et al., 2000). Because of a variety of barriers, vulnerable populations are at higher risk of poor health and health outcomes (Aday, 1994). While the behavioral model of healthcare utilization conceptualizes access in general terms, the behavioral model for vulnerable populations adapts for the differences in access due to vulnerabilities (Aday, 1994; Gelberg et al., 2000). To address the differences between vulnerable and other populations, the vulnerable population model differentiates between traditional and vulnerable domains within predisposing characteristics, enabling resources and needs when predicting healthcare utilization (Figure 3) (Gelberg et al., 2000). Additionally, the behavioral model for vulnerable populations includes health behaviors as contributing information for healthcare utilization (Gelberg et al., 2000).



Traditional Domains

Demographics
- Age
- Gender
- Marital Status

Health Beliefs
- Values concerning health and illness
- Attitudes toward health services
- Knowledge about disease

Social Structure
- Ethnicity
- Education
- Employment
- Social networks
- Occupation
- Family size
- Religion

Personal/Family Resources
- Regular source of care
- Insurance
- Income
- Social support
- Perceived barriers to care

Community Resources
- Residence
- Region
- Health services resources

Perceived Health
- General population health conditions

Evaluated Health
- General population health conditions

Personal Health Practices
- Diet
- Exercise
- Self-care
- Tobacco use
- Adherence to care

Use of Health Services
- Ambulatory care
- Inpatient Care
- Alternative healthcare
- Long-term care

Vulnerable Domains

Social Structure
- Country of birth
- Acculturation/Immigration/ Literacy

Sexual orientation

Childhood characteristics
- Residential history/homelessness
- Living conditions
- Mobility
- Length of time in the community
- Criminal behavior/Prison history
- Victimization
- Mental Illness
- Psychological resources
- Substance abuse

Personal/Family Resources
- Competing needs
- Hunger
- Public benefits
- Self-help skills
- Ability to negotiate system
- Case manager/Conservator
- Transportation
- Telephone
- Information sources

Community Resources
- Crime rates
- Social services resources

Perceived Health
- Vulnerable population health conditions

Evaluated Health
- Vulnerable population health conditions

Personal Health Practices
- Food sources
- Hygiene
- Unsafe sexual behaviors

Traditional/ Vulnerable Domains

Health Status
- Perceived health
- Evaluated health

Satisfaction with care
- General satisfaction
- Technical quality
- Interpersonal aspects
- Coordination
- Communication
- Financial aspects
- Time spent with clinician
- Access/availability/ convenience
- Continuity
- Comprehensiveness
- Administrative hassle

Figure 3. The behavioral model for vulnerable populations.

Source: Gelberg, L., Andersen, R.M., and Leake, B.D., *HSR:Health Services Research* 2000;34:6 p.1278

In addition to the usual predisposing characteristics of age, race, gender, marital status and health beliefs, the vulnerable domain contains other measures of social structure such as immigration status, literacy levels, sub-standard living conditions, criminal or high risk behaviors, and childhood history related to neglect, abuse or non-traditional living arrangements (Figure 3) (Gelberg et al., 2000). Enabling resources for vulnerable populations would include measures of competing needs, public benefits and availability of other relevant community resources such as transportation (Figure 3) (Gelberg et al., 2000). Finally, differences in needs for vulnerable populations include concerns related to increased incidence of conditions such as sexually transmitted disease, chemical abuse, and mental health status. While some of these factors are normally considered part of the predisposing health status group of variables, for vulnerable populations they are more appropriately placed in the needs category of healthcare care utilization predictors (Figure 3) (Gelberg et al., 2000).

Conceptualization of utilization for PPH with HAIs

In developing a conceptual model to identify and measure relationships for this study, it was important to build upon a model that fit the hypothesized chain of events. Given the hypothesized chain of events as increased insurance coverage leading to increased preventive care utilization leading to decreased PPH and associated HAI, I first defined the primary outcome measure as PPH. With the primary outcome measure identified, it became evident that an appropriate explanatory model must identify health outcomes in terms of access giving adequate consideration to other causal variables related to the uninsured. Since the uninsured and underinsured are considered vulnerable

populations, the behavioral model for vulnerable populations uses outcomes such as perceived and evaluated health status, and the model considers characteristics such as insurance status in predicting outcomes, the behavioral model for vulnerable populations was an appropriate basis for evaluating the research question (Aday, 1994; Bindman, Chattopadhyay, & Auerback, 2008a; Gelberg et al., 2000).

Identification of PPH for this study was based upon deidentified administrative discharge data. As such, the ability to tease out variation in utilization is limited to information in the discharge record and other information sources that can be linked at the hospital or community level. With this limitation in mind, I developed the following conceptual model to capture variation in utilization using the individual as the unit of analyses (Figure 4). Building on the behavioral model of healthcare utilization and the behavioral model for vulnerable populations, the model incorporates the most meaningful individual and community measures to reflect important predisposing characteristics, enabling resources, and needs. Where possible, measures reflecting vulnerability were included. For example, availability of public benefits was captured using the variable for Health Services Region (HSR), county of residence and administration of health services to create two public benefits variables. Since public benefits vary by HSR in Texas, the administrative regions were used as a proxy for available services. Additionally, availability of services can be measured through distance to public health service offices. As a proxy for distance to public benefits, the second public benefits variable categorized distance to services by identifying county of residence as containing an HSR office, a county public health office, or no public health

offices. By accounting for these variations, I intended to generate the most accurate reflection of how payer policies affect utilization of healthcare for PPH admissions.

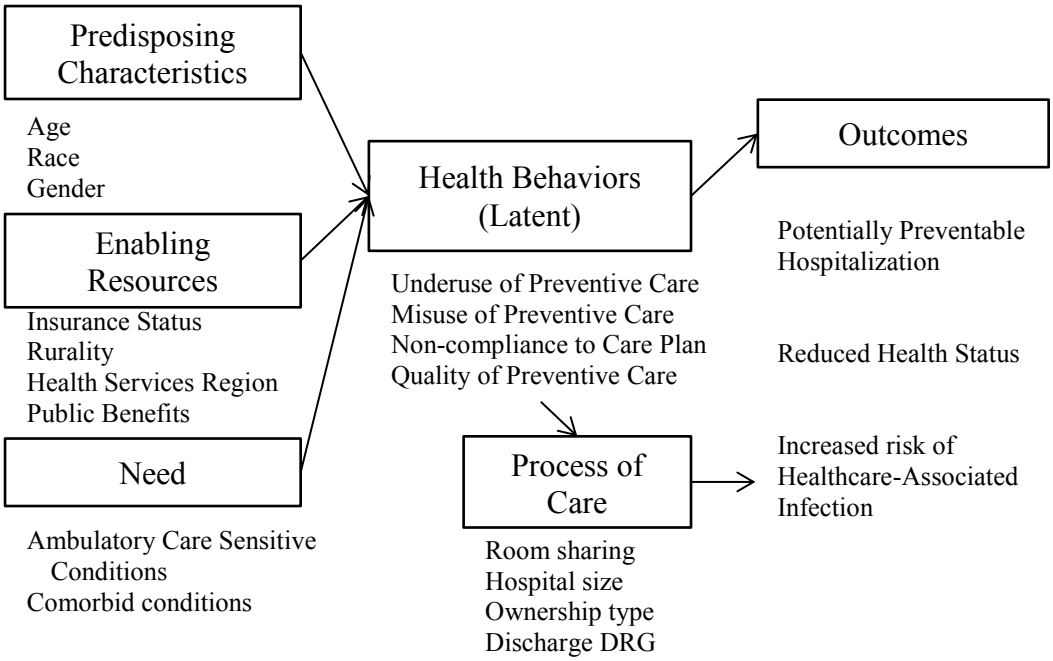


Figure 4. Conceptual model of healthcare utilization for potentially preventable hospitalizations with healthcare-associated infections

CHAPTER IV

METHODS

Any hospitalization exposes patients to the risk of an HAI, but for an individual admitted for PPH, the exposure to HAI risk is by extension also potentially preventable. Given the implementation of the ACA, the identified relationship between insurance status and PPH, what little is known about individuals admitted with a PPH and acquire an HAI, my hypothesize question is: following the full implementation of the ACA, will the increase in preventive care cost attributable to improved insurance coverage for individuals with ACSCs be offset by reductions in costs associated with reduced rate of HAI during a PPH? To answer this question and facilitate the primary goals of my thesis, to ascertain the incidence of the co-occurrence of a PPH and an HAI during one inpatient stay, and to estimate the costs attributable to an HAI during a PPH, I have developed the following four specific aims for my thesis research:

Specific Aim 1 Quantify the incidence of PPH and HAI in Texas, identifying characteristics of the PPH, HAI, and PPH with HAI populations.

Specific Aim 2 Estimate costs associated with PPH and the incremental cost of HAI during hospitalization.

Specific Aim 3 Estimate total utilization and costs for PPH, PPH with HAI, and preventive healthcare for insured individuals with similar ACSCs and no PPH using private insurer claims data.

Specific Aim 4 Examine the differences in prevalence and cost for the insured and uninsured.

With the ultimate goal of answering the hypothesis question, each of the specific aims fulfills a goal. The goal of specific aim one is to identify and quantify how individuals with a PPH, HAI and PPH with HAI differ from one another and the rest of the inpatient population. Specific aim two provides us with a base measure of hospitalization cost and the incremental cost differences for PPH and PPH with HAI. Specific aim three uses the BCBSTX claims data to generate the remaining cost estimates needed to answer the hypothesis question. To answer the hypothesis question we need preventive care costs and the incremental cost of the additional care required after hospitalization, in particular incremental costs for HAI. For the non-PPH ACSC population, estimated preventive care costs potentially reflect the cost of healthcare required to control ACSC. The second cost included the cost of preventive care used by individuals prior to a PPH. The final cost generated as part of specific aim three is the post-hospitalization healthcare utilization for the PPH population. An additional component of the post-hospitalization cost is to differentiate between PPH and PPH with HAI populations in order to calculate the total incremental cost associated with and HAI for the PPH population. Finally, since the analytic focus is access through insurance, specific aim four examines all costs estimates through the lens of primary payer to determine the role insurance status and the type of insurance play.

Data

Texas Hospital Inpatient Discharge Public Use Data File, 2011

The 2011 Texas Hospital Discharge Public Use Data File (PUDF) contains more than 2.9 million summary abstracts of patient level information from administrative

forms reflecting care provided during hospital stays in one of 576 Texas hospitals(Texas Health Care Information Collection, 2013). While the majority of Texas hospitals are required to report discharge summary data to the Texas Health Care Information Collection (THCIC), under Chapter 108 of the Texas Health and Safety Code, there are hospitals that are exempt. Exemptions account for 46 Critical Access Hospitals and 34 other hospitals in Texas that meet one of the following criteria:

- Located in a county with less than 35,000 people
- Hospital in a United States Census Bureau defined rural county with more than 35,000 people and less than 100 licensed hospital beds
- Hospital that does not receive payment from insurers or government funds for care

  (Texas Department of State Health Services, 2011; Texas Health Care Information Collection, 2014).

For hospitals that do report, information was collected with the uniform bill (UB-92) or the THCIC 837 format. Data elements reflect patient discharge quarter, length of hospital stay in days, patient demographic information, ICD-9-CM codes for up to 25 diagnoses with corresponding present on admission information, up to 25 procedure codes with day the procedure occurred during the hospitalization, anticipated payer information, and charges associated with the inpatient stay. Of the 576 hospitals that reported inpatient discharge summary, 34 were Critical Access Hospitals, and 29 hospitals included discharges from other hospital facilities affiliated with the reporting hospital (Texas Health Care Information Collection, 2014).

National Health Safety Network and Texas Department of State Health Services annual report on health care-associated infections

While the National Health Safety Network (NHSN) warehouses the most healthcare associated infection (HAI) surveillance information in the United States, it does not share event detailed data for analyses. It does publish annual reports reflecting Standardized Infection Ratios (SIRs) and state based aggregated data. Aggregated information includes number of events in each state, number of events in HAI relevant departments, and number and types of facilities reporting (Dudeck et al., 2013).

Mandated reporting of certain HAIs began in 2012 for Texas hospitals. With a focus on central line-associated bloodstream infection and surgical site infection, hospitals also report other HAI information through NHSN's electronic reporting system. While Texas uses NHSN as the initial repository and collection mechanism for its HAI information, it also provides additional validation checks when it downloads data from NHSN into the Texas HAI data warehouse known as the Texas Health Care Safety Network (TxHSN) (Vinyard, 2013).

Blue Cross/Blue Shield of Texas claims data, 2010-2012

Available for years 2008 to 2012, the Blue Cross/Blue Shield of Texas (BCBSTX) claims data includes information for over 3 million enrollees (University of Texas School of Public Health, 2012). Warehoused at the University of Texas Health Science Center at Houston, the claims data includes variables reflecting enrollee demographics, dates of service, billed, allowed and paid amounts, diagnoses and procedures reflected by ICD-9-CM codes, Healthcare Common Procedure Coding

System (HCPCS) and diagnosis related group (DRG) codes. Just over 30 thousand BCBSTX enrollees were excluded from the evaluation due to participation in a managed care or capitated payment structure. These enrollees were excluded due to incomplete information about healthcare utilization across the continuum of care.

Centers for Medicare and Medicaid Services cost reports

Medicare certified hospitals are required to annually report facility information, utilization, and comprehensive cost and charge data to the Healthcare Cost Report Information System (HCRIS)(Centers for Medicare and Medicaid Services, 2013b). The information collected from hospitals on form CMS-2552-10 and reported through Medicare Administrative Contractors are available for download from the Centers for Medicare and Medicaid Services (CMS) website (Centers for Medicare and Medicaid Services, 2013c). Hospital cost reports updated quarterly and available for 1996 to 2013 include schedule C of form CMS-2552-10. Schedule C includes the cost and charge information necessary to calculate hospital specific cost-to-charge ratios. CMS provides a publically available file that includes hospital Medicare identification number, fiscal year beginning and ending dates and the cost and charge variables reported in schedule C including total costs, total inpatient charges, and total outpatient charges. Not all hospital fiscal calendars align with a calendar year, therefore CMS cost report data from 2010, 2011, and 2012 were used to create a proportionally weighted 2011 cost-to-charge ratio.

Also available in the CMS cost reports are the number of licensed beds by Medicare identifier. Where number of beds were missing, the values were imputed using

an estimation of average daily hospital census from the PUDF and the 2011 staffed bed occupancy rate reported by the Texas Department of State Health Services (Center for Health Statistics - Hospital Survey Unit, 2013).

Data management

Although all data described was deidentified and contained no personal identifiers, data was stored, utilized, and reported using methods consistent with data that includes personal identifiers. Methods include secure storage and aggregate reporting of results. Data transfer adhered to security protocol measures as defined by the owner of the data. While the study data and protocols meet the definitions of exempt status research, Institutional Review Board (IRB) approval from Texas A&M Research Compliance was obtained.

Identification of potentially preventable hospitalizations and comorbid conditions

Using SAS® version 9.3, PPH were identified from the PUDF using SAS® programs PQSAS1and PDSAS1 from the AHRQ Prevention Quality Indicator and Pediatric Indicator, version 4.5 websites (Agency for Healthcare Research and Quality, 2013c). PQSAS1 is one of a suite of programs in the Prevention Quality Indicator (PQI) zipped file used to identify the discharges with one of 14 PPH and calculate rates of occurrence by geographic area. PPH for children are identified through the Pediatric Quality Indicator (PDI) programs. For the purposes of this research only the PQI and PDI programs necessary to identify PPH discharges were modified as specified by the software instructions (Batelle, 2013).

Comorbidity software also included in the AHRQ Quality Indicator software identifies 30 comorbid conditions from the discharge data (Agency for Healthcare Research and Quality, 2013a; Elixhauser, Steiner, Harris, & Coffey, 1998).

Identification of healthcare associated infections

To facilitate the analyses proposed, the following definitions of HAI have been identified from the literature and other known and validated methods of identifying HAI from inpatient discharge data. With no definitive or validated methods available for SSI, CAUTI, and VAP, as suggested by Jhung et. al, (2009), I used data with as many diagnosis fields as possible, a combination of codes, and validated findings where possible against the TxHSN data. I also consolidated ICD-9-CM codes used to identify infections and procedures from other studies (Jhung & Banerjee, 2009; Sherman et al., 2006; Stevenson et al., 2008). Figure 5 is a data flow diagram representing the process for identifying the PPH and HAI from the 2011 THCIC inpatient PUDF.

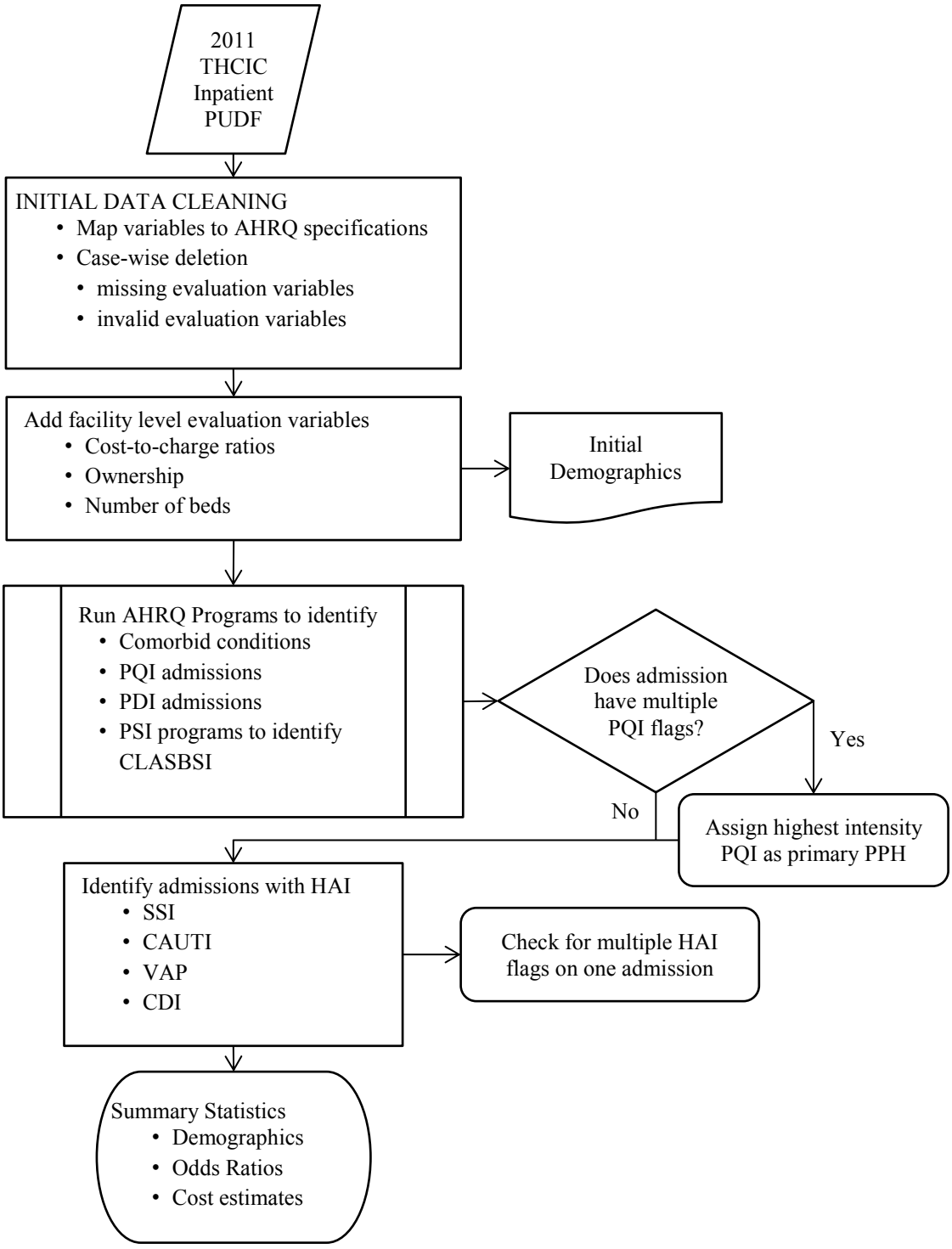


Figure 5. Data flow to identify PPH and HAI from administrative discharge data

Surgical site infections (SSI)

While no definitive or validated methods are available for identifying SSI from administrative data, the Centers for Disease Control and Prevention (CDC) does provide a publically available list of ICD-9-CM codes to identify procedures associated with SSI including 10 cardiac bypass graft surgery codes, 10 hip prosthetic codes, and 7 knee prosthetic codes listed in the Appendix (Centers for Disease Control and Prevention, National Center for Emerging and Zoonotic Infectious Diseases, & Division of Healthcare Qualtiy Promotion, 2014). Since the definition of SSI includes infections that occur up to 90 days after surgery, identifying hospitalizations for SSI from the PUDF are limited to infections that occur within the hospitalization. While infections can be identified within the initial hospitalization, these are usually of the superficial nature. Following the methods of Sherman et al. (2006) and Stevenson et al.(2008), infections codes listed in the Appendix that were not present on admission were used in combination with the CDC procedure codes to identify SSI (Figure 6) (Centers for Disease Control and Prevention, National Center for Emerging and Zoonotic Infectious Diseases, & Division of Healthcare Qualtiy Promotion, 2014; Sherman et al., 2006; Stevenson et al., 2008).

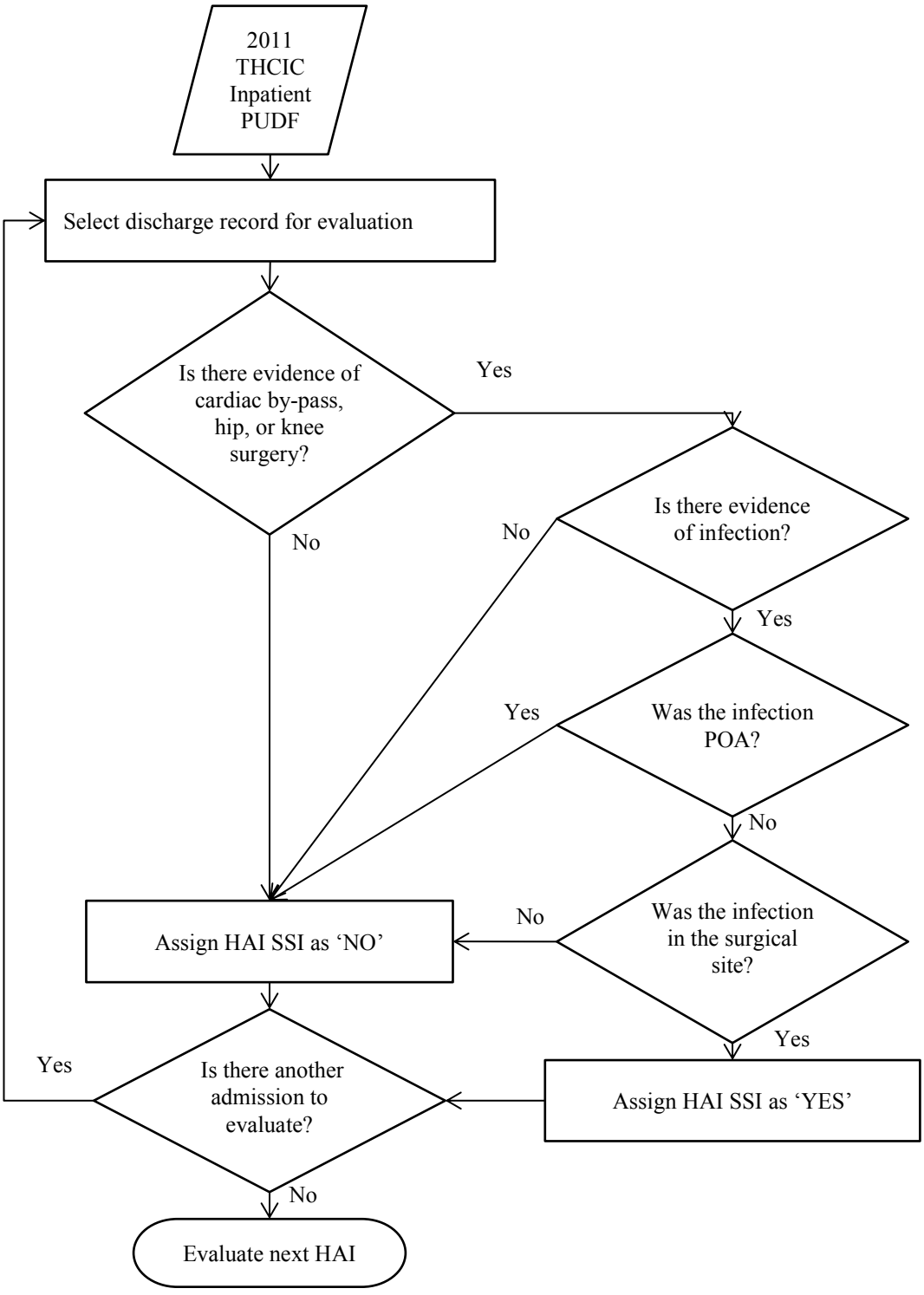


Figure 6. Identification of HAI from administrative inpatient data, SSI

Catheter associated urinary tract infection (CAUTI)

To identify CAUTI, no procedure codes have been identified for catheterization or removal during a hospitalization. However, there is one code, 996.64 for complication related to infection from an indwelling catheter. Unfortunately, the literature demonstrates an underreporting of CAUTI if this code alone is used for identification. In an effort to capture an accurate measure of CAUTI, 17 infection codes were identified and used in combination with ICD-9-CM code 996.31 (Agency for Healthcare Research and Quality, 2013b; Sherman et al., 2006). Code 996.31 represents mechanical complications due to an indwelling catheter. Since the likelihood of a CAUTI increases the longer it is in place, a discharge was classified as a CAUTI if code 996.64 was present, or code 996.31 was listed with one of the 17 infection codes where the infection was not present on admission and the estimated duration of catheterization was longer than two days (Figure 7) (Centers for Disease Control and Prevention, National Center for Emerging and Zoonotic Infectious Diseases, & Division of Healthcare Quality Promotion, 2014a). Infection codes for CAUTI are listed in the Appendix.

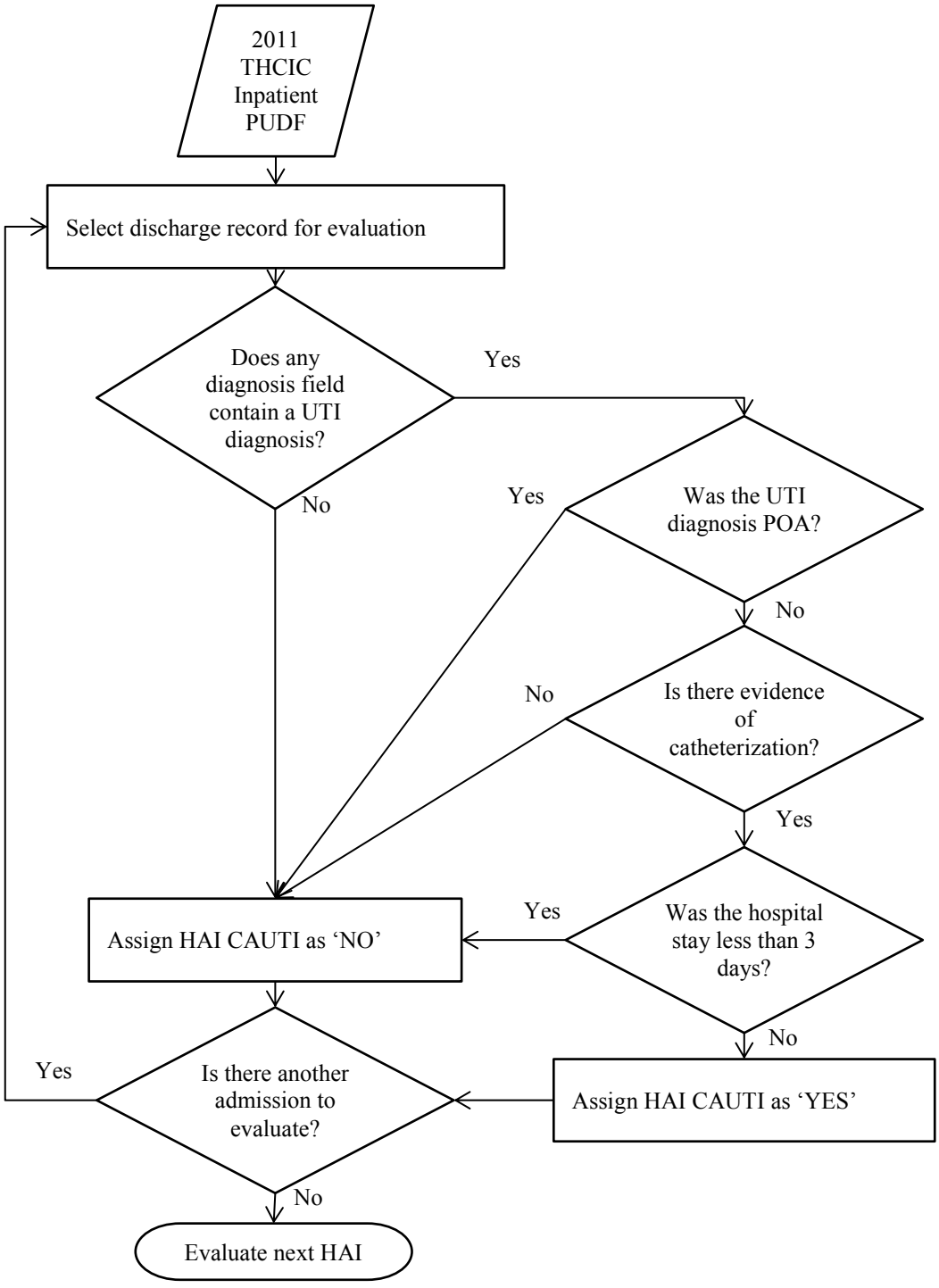


Figure 7. Identification of HAI from administrative inpatient data, CAUTI

Ventilator associated pneumonia (VAP)

To assign a discharge as having VAP, four things were evaluated. First, diagnoses fields were examined for the presence of diagnosis code 997.31, ventilator associated pneumonia. Since this code historically underreports VAP, the next item evaluated was codes for mechanical ventilation or intubation (Restrepo et al., 2010; Stevenson et al., 2008). Once mechanical ventilation was identified, diagnoses codes were evaluated for one of 29 pneumonia type infections not present on admission (Sherman et al., 2006; Stevenson et al., 2008). Finally, duration of ventilation was calculated. An admission was determined to have VAP with a diagnosis code of 997.31 or the presence of mechanical ventilation for more than 4 days and a pneumonia type infection that was not present on admission (Figure 8) (Centers for Disease Control and Prevention, National Center for Emerging and Zoonotic Infectious Diseases, & Division of Healthcare Quality Promotion, 2014b). Infection and procedure codes for VAP can be found in the Appendix.

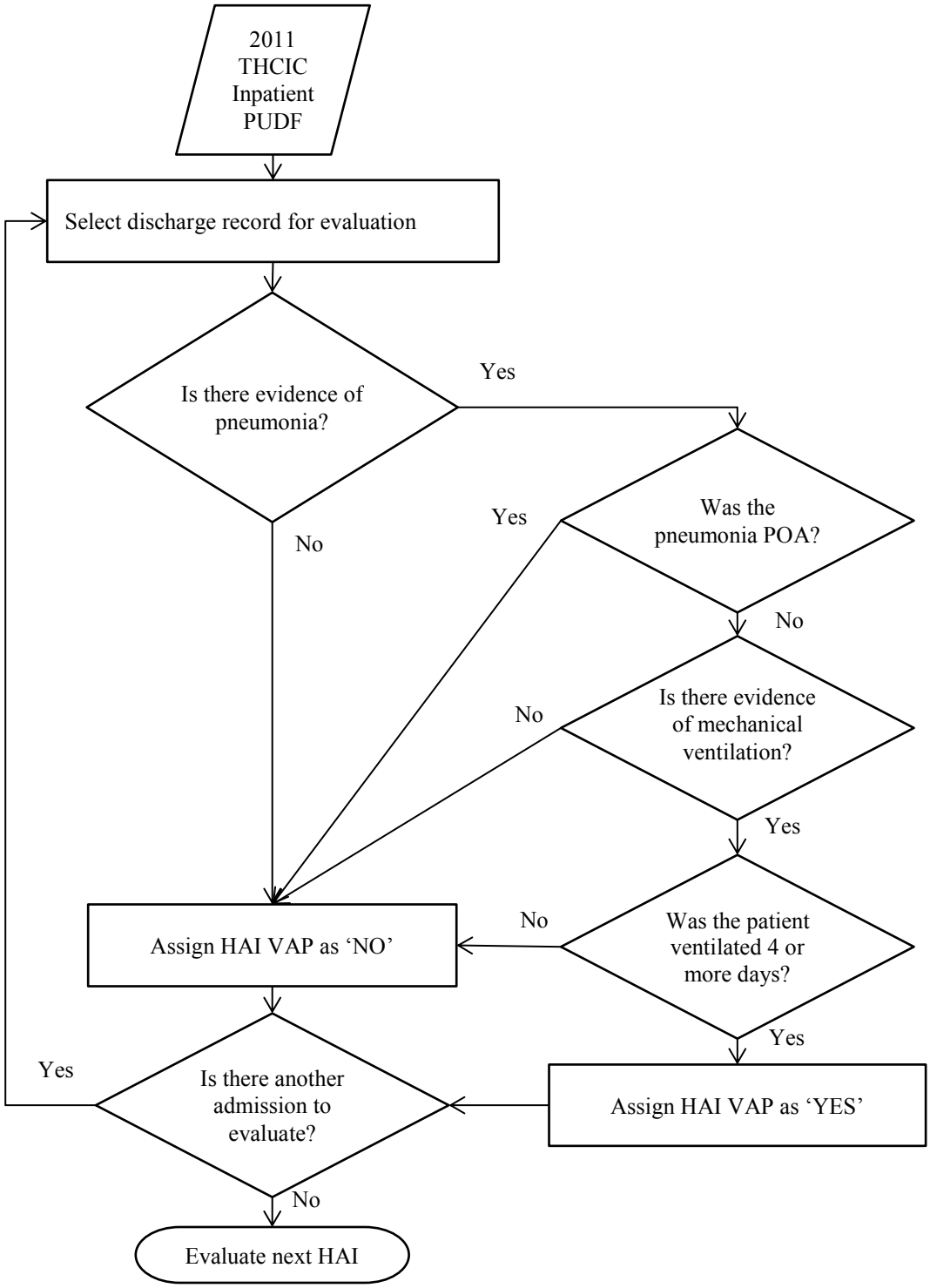


Figure 8. Identification of HAI from administrative inpatient data, VAP

Central line-associated blood stream infections (CLABSI)

Also considered a patient safety issue that can be identified from inpatient discharge data, AHRQ has included in its Quality Indicator modules three indicators to identify CLABSI. From the Patient Safety Indicator (PSI) module, I used the definition associated with PSI 7 – central venous catheter-related blood stream infection rate (Figure 9). To identify CLABSI in children, I used two indicators from the Pediatric Quality Indicator (PDI) module including PDI 12 – central venous catheter-related blood stream infection rate for patients 3 months through 17 years of age and NQI 3 – neonatal blood stream infection rate for neonates. All three measures are National Quality Forum endorsed measures of CLABSI (Department of Health and Human Services, 2013; National Quality Forum, 2013).

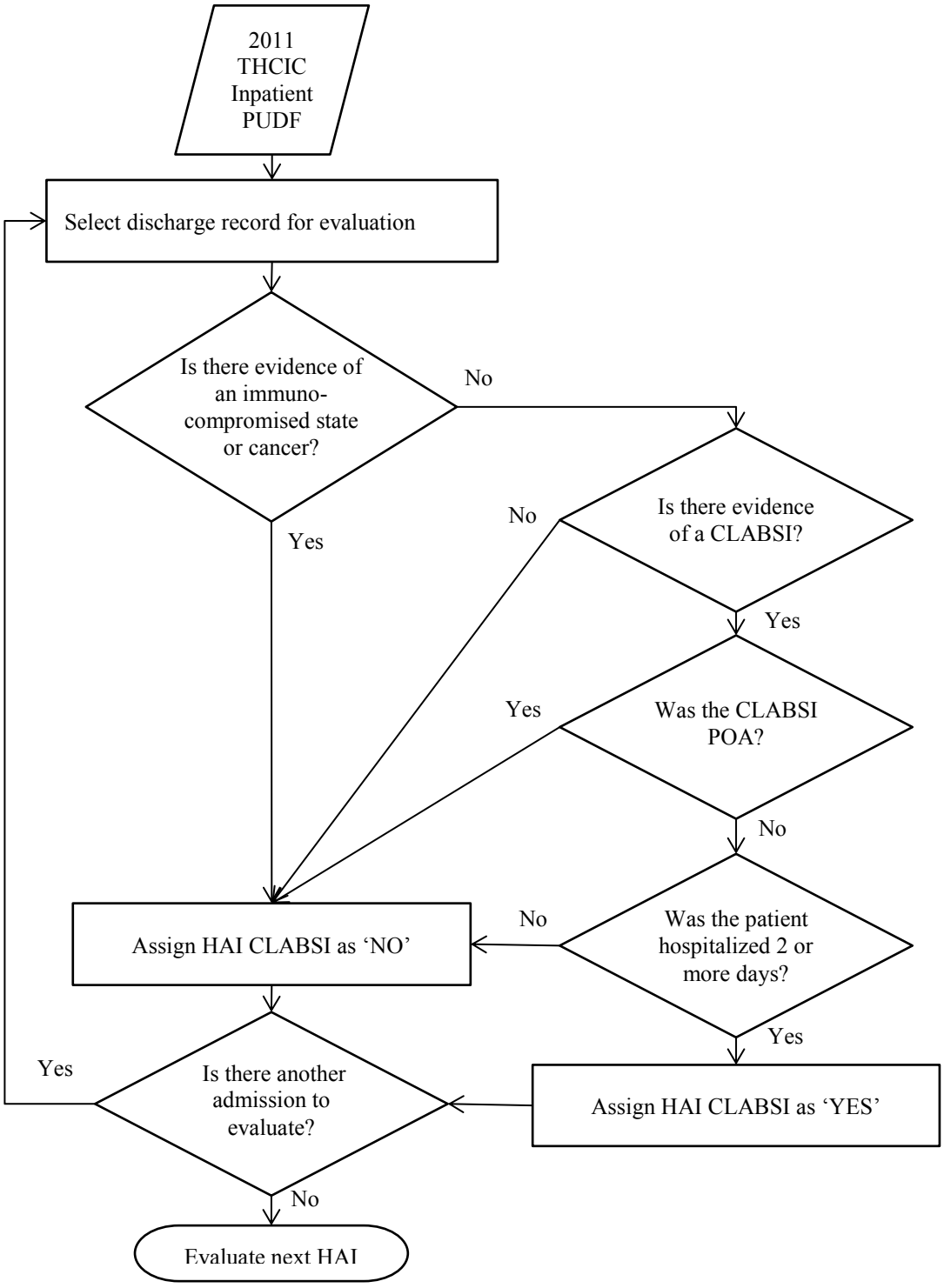


Figure 9. Identification of HAI from administrative inpatient data, CLABSI

Clostridium difficile infection (CDI)

Clostridium difficile infection (CDI) can be identified from the PUDF by using an ICD-9-CM diagnosis of 008.45 in any of the 25 diagnosis field variables. A discharge with a diagnoses of CDI was considered an HAI if not present on admission and hospital length of stay was greater than two days (Figure 10).

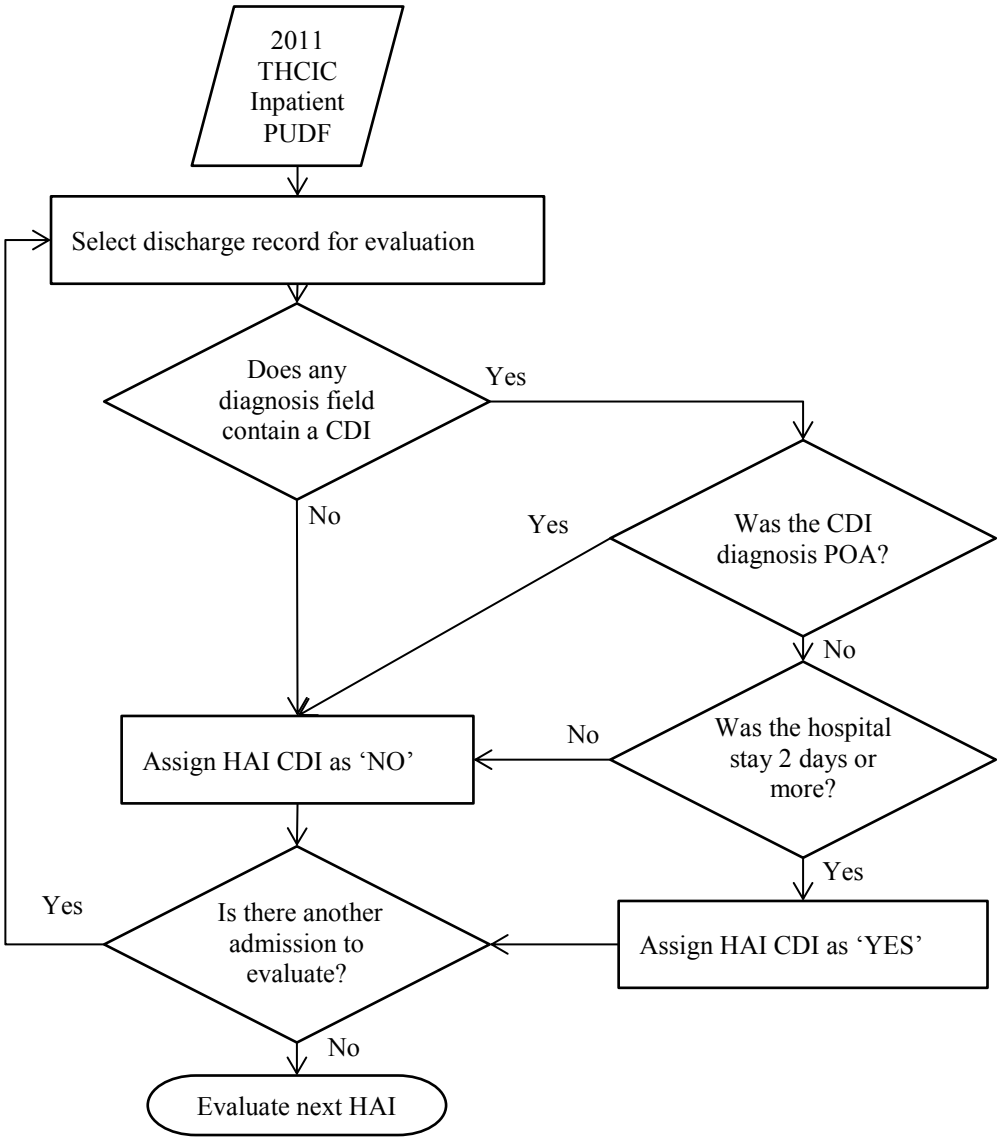


Figure 10. Identification of HAI from administrative inpatient data, CDI

Exclusion criteria

Discharge records were excluded from evaluation when age, gender, race, primary payer, or principal diagnosis codes were missing or invalid. While I did not want to lose valuable information about the effect PQI and HAI have on length of stay (LOS), I also did not want LOS outliers to exert disproportionate influence on estimates drawn from the study data. Therefore, I excluded patients with LOS greater than 180 days as I considered them extreme LOS outliers (three standard deviations above the mean LOS was 36 days). The PQIs for perforated appendix were excluded as there is no ACSC that precedes appendicitis, and hospitalization is required for treatment. While perforation may be avoided with timely care, hospital care is part of successful treatment protocol. Finally, I eliminated PPH with less than five HAI from extensive evaluation due to the inability of statistical analyses to make meaningful inferences about the population.

Incidence and odds ratios of PPH with HAI

To address specific aim 1, I used data mapping conventions from the AHRQ Quality Indicator package for age, race and gender, the PQI programs, and the above definitions of HAI to estimate the incidence of PPH and HAI. Once identified, potentially significant relationships were identified through a correlation matrix including PPH, HAI, and other independent variables. Additionally, preliminary analyses included bivariate regression between the outcome variables cost and the probability of an HAI with each independent variable. Odds ratios were calculated for each PQI and HAI combination adjusting for the effects of age, gender, race, health

status as measured by the vector of comorbid conditions, healthcare characteristics such as hospital ownership, hospital size, and the additional risks associated with sharing a room for HAI, and community characteristics such availability of public benefits, distance to services, and rurality. The following model was specified to generate the odds ratios and standard errors using SAS® 9.3.

$$logit\left(P_{i,hai}\right) = \beta_1 age_i + \beta_2 gender_i + \beta_3 race_i + \beta_4 PQI_{i,j} + \beta_5 \boldsymbol{health\ status}_i + \beta_6 \boldsymbol{hospital\ characteristics} + \beta_7 \boldsymbol{community\ characteristics}_i + \varepsilon_i$$

Where

i = i^{th} patient

hai = HAI odds ratio being estimated

$\beta_{1 \text{ thru } 6}$ = coefficients for corresponding variables

age = patient age group at discharge

gender = patient gender

race = patient's reported race category

health status = vector of comorbid conditions

hospital characteristics = vector including room type (private, semi-private or ward room), average daily census of hospital, hospital ownership

community characteristics = vector including rurality, administrative Health Service Region, location of public health benefits (HSR office in county, county public health, no public service office within county of residence)

ε_i = error term associated with individual *i*

$PQI_{i,j}$ = indicator variable for patient *i* with PQI_j,

where *j* = one of the PQIs.

I excluded relevant comorbid conditions from the regression models when the PQI under evaluation was similar to the comorbid condition. For example, I excluded the comorbid condition diabetes from the regression models when evaluating the PPHs for short-term complication due to diabetes, long-term complications due to diabetes, and diabetes related lower-extremity amputation.

Identifying ACSC utilization from BCBSTX claims data

To meet specific aim 3, an estimation of preventive care costs for the PPH population and the non-PPH ACSC population were necessary. Additionally, an estimation of follow-up care cost was necessary including the differentiation between follow-up care cost for the underlying ACSC and follow-up costs associated with acquisition of an HAI. To identify PPH associated costs, I used the BSBCTX claims data by identifying relevant beneficiaries following similar methods to those used with the PUDF to assure comparability of information obtained. First, institutional claims indicating hospitalization during 2011 followed the same process depicted in Figure 5. Next, the AHRQ Quality indicator programs flagged PPH admissions and comorbid conditions. Finally, I applied the definitions for HAI to identify admissions with HAI.

Once I identified hospitalizations for PPH, HAI, and PPH with HAI, the relevant unique patient identifiers acted as the identifier for other utilization claims across the continuum of care. For the PPH population, I identified two categories of utilization and costs, pre-hospital preventive care and post-discharge follow-up care. Pre-hospital preventive care for the PPH population included physician visits, outpatient visits, lab fees, and medications for six months prior to admission date. Follow-up utilization included physician visits, outpatient visits, lab fees and medications for six months post-discharge. Two limitations existed within the BCBSTX data. First, limitations existed in the ability to quantify costs and utilization for beneficiaries over age 65. Since most individuals over age 65 years are assumed to participate in Medicare, I assumed the BCBSTX claims were supplemental to Medicare coverage. Second, not all BCBSTX beneficiaries have pharmaceutical coverage, therefore estimations of pharmaceutical use and cost are assumed to be under-reported.

For the ACSC population, I identified ten ACSC conditions consistent with the PPH identified by the AHRQ PQI. For example, PQI 1, 3, 14, and 16 identify short-term, long-term, uncontrolled, and lower-extremity amputation related to the ACSC of diabetes. The ACSC conditions included diabetes, chronic obstructive pulmonary disease, asthma, heart failure, hypertension, angina, urinary tract infection, dehydration, pneumonia, and prenatal care. With the exception of prenatal care, diagnosis codes identifying ACSC came from the AHRQ technical specifications for the PQI or the CMS Chronic Condition Warehouse condition categories (Agency for Healthcare Research and Quality, 2013a; Buccaneer, 2014). Prenatal care identification followed pre-natal

care diagnoses codes as specified by Blue Cross/ Blue Shield (BlueCross BlueSheild of Texas, 2014). When identifying beneficiaries with ACSC conditions, I excluded individuals with hospitalizations within the study period, 2011, with the exception of prenatal care, since delivery related hospitalization is normal. However, I did exclude beneficiaries from the prenatal ACSC population for non-delivery related hospitalizations.

Similar to the PPH, HAI, and PPH with HAI groups, I identified preventive healthcare utilization for physician visits, outpatient visits, lab fees, and medications using the unique patient identifier. With the diagnoses codes for each ACSC, claim lines associated with each ACSC were identified and summarized by beneficiary as illustrated in Figure 11.

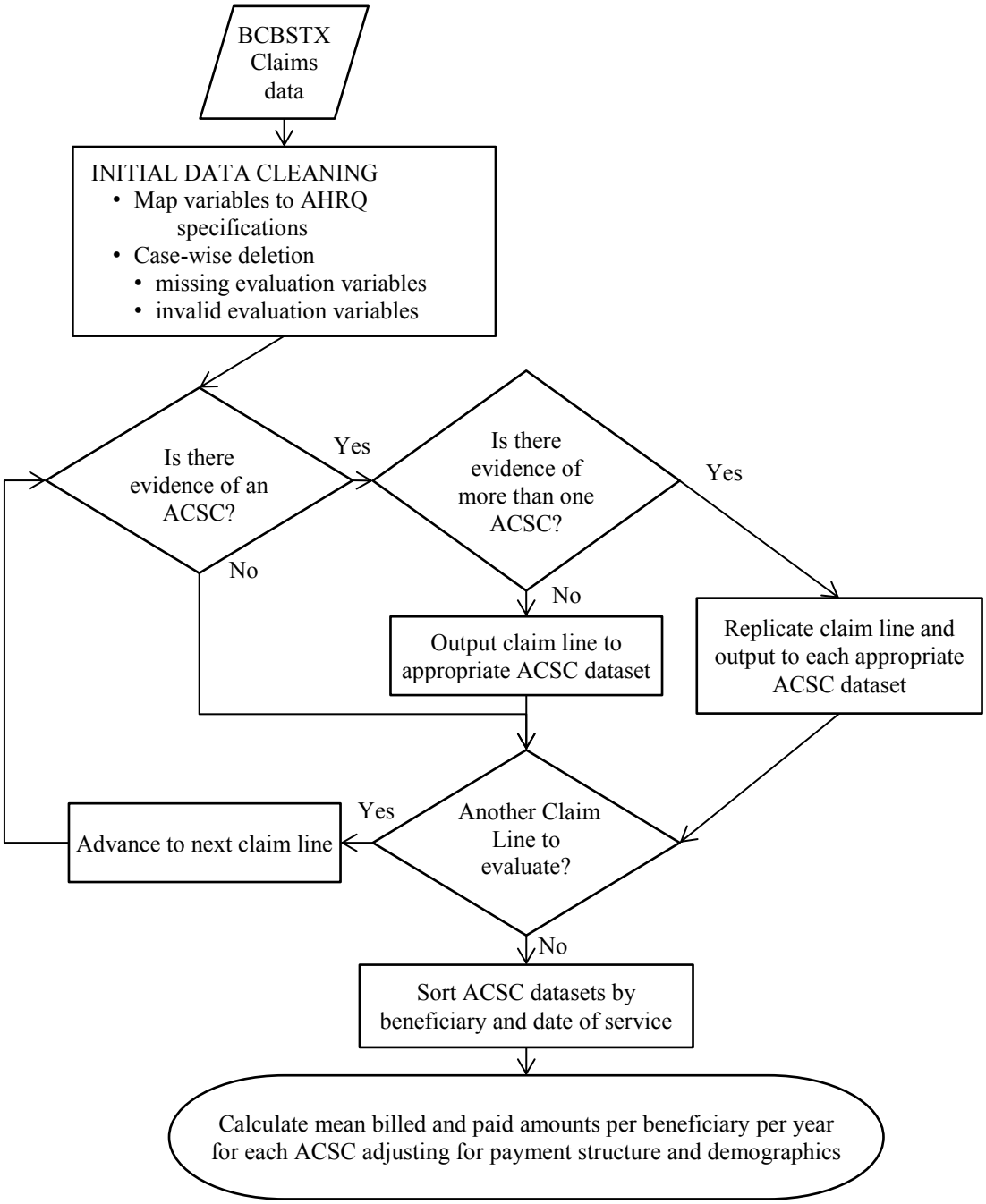


Figure 11. Data flow to identify ACSC utilization with the BCBSTX data.

Cost

Identifying cost for inpatient discharge data

Cost-to-charge ratios

Needed to estimate costs from the PUDF and fulfill specific aim 2, I used total costs, total inpatient charges and total outpatient charges from the CMS cost reports to calculate cost-to-charge ratios. Medicare identification numbers corresponding to the acute care facilities listed in Texas were used to identify all necessary data from the CMS abstracts of Schedule C.

A hospital specific cost-to-charge ratio was calculated with the following formula:

$$Cost - to - charge\ ratio = \frac{Total\ Costs}{Total\ inpatient\ charges + Total\ outpatient\ charges}$$

Because both inpatients and outpatients utilize some hospital cost centers, and costs on Schedule C are reported collectively, limitations arise in using only inpatient charges in calculating a cost-to-charge ratio. To account for this limitation, the sum of total inpatient charges and total outpatient charges were used in the denominator. Additionally, not all hospital fiscal calendars align with a calendar year, therefore CMS cost report data from 2010, 2011, and 2012 were used to create a proportionally weighted 2011 cost-to-charge ratio. Where cost reports were unavailable for the full year, the partial year cost-to-charge ratio was used to estimate costs for the entire year since cost-to-charge ratios do not change drastically from year to year. For hospitals with no cost or charge information, the median Texas hospital-specific cost-to-charge ratio

was assigned for the purpose of estimating cost of hospital care. The median cost-to-charge ratio was selected over the mean as a more representative measure of centrality for the distribution of Texas hospital cost-to-charge ratios.

Total and incremental costs

To generate the cost estimates necessary to fulfill specific aim 2, a cost estimate of each discharge in the PUDF was necessary. To estimate total costs for each discharge, the total charges were multiplied by the facility specific cost-to-charge ratio. Once estimated costs were identified for all discharges, mean costs were calculated for each mutually exclusive group of PPH, HAI, and PPH with HAI. To quantify variation within the general inpatient population, I used a generalized linear regression model that adjusted for age, race, gender, health status, hospital characteristics, and community characteristics to estimate mean hospitalization cost and the incremental differences associated with PPH, HAI and payer type. By pulling out differences by payer in the cost models, I partially address specific aim 4.

Identifying costs from BCBSTX claims data

Since claims data includes billed, allowed and payment information, for each ACSC, a range of mean annual preventive care payments were estimated for patients with and without a PPH. Cost estimates of preventive care for the PPH and ACSC groups were necessary to identify within payer variation. For patients with no PPH in 2011, mean preventive care payment consisted of 2011utilization. For patients with a PPH in 2011, mean preventive care payment included utilization for six months prior to

the PPH event. To account for the effects of age, gender, health status, and payment structure the Generalized Linear Regression model specified the following:

$$preventive\ care\ cost_{pph,i} = \beta_1 age_i + \beta_2 gender_i + \beta_3 \boldsymbol{health\ status}_i + \beta_4 plan\ type_i + \varepsilon_i$$

Where

pph	= PPH group (PPH/no PPH)
i	= i^{th} patient
$\beta_{1 \text{ thru } 4}$	= coefficients for corresponding variables
age	= patient age group at discharge
gender	= patient gender
health status	= vector of comorbid conditions defined by the AHRQ comorbidity measures
plan type	= BCBS structure of PPO or PPO+
ε_i	= error term associated with individual *i*

In using the AHRQ comorbidity measures in the cost model, I accounted for health status and additional risk factors such as obesity or depression. Since ACSC conditions are frequently considered comorbid conditions for other health issues, the condition was not included in the regression model as a comorbidity when it was defined as the ACSC of interest (Braunstein et al., 2003; Chang, Weiner, Richards, Bleich, & Segal, 2012; Mokdad et al., 2003; Wolff, Starfield, & Anderson, 2002). For example,

when estimating the preventive care cost for diabetes, the comorbidity variable for diabetes was not included in the regression model. Additionally, within an ACSC population, if a comorbid condition was not identified within the population, it was not included in the regression model. For example, when estimating an adjusted mean for diabetes, if no diabetes patients had depression, depression was not be included in the model. By using this approach, relevant health status information was included without over specification of the regression model.

The cost estimates fulfill specific aim 3, and facilitate answering the research question by providing proxy costs of healthcare for the uninsured population with an ACSC, a PPH or a PPH with HAI.

Comparison of preventive care costs to incremental HAI costs

To answer the hypothesis question, I needed to calculate the anticipated difference in two costs: the incremental increase in preventive care costs for the uninsured ACSC population after attaining insurance and incremental HAI costs for the uninsured individuals with PPH and HAI. For the preventive care calculation, I used the estimated mean preventive care cost for each ACSC within the non-hospitalized BSBCTX population and multiplied it by the uninsured population estimated with each ACSC. For an accurate reflection of the increased cost of preventive care, I needed to estimate and subtract the amount of healthcare potentially consumed by the uninsured for ACSC and PPH. I accomplished this by first subtracting the identified number of uninsured with a PPH from the estimated uninsured ACSC population in Texas. Then the estimated number of uninsured individuals with an ACSC and no PPH was

multiplied by the estimated cost of preventive services used by the BCBSTX PPH population. The BCBSTX PPH preventive care cost acts as a proxy that reflects similar utilization by the uninsured. For the uninsured with a PPH, I added six months of BCBSTX PPH preventive care cost to six months of BCBSTX PPH follow-up cost and the cost of a PPH for each ACSC condition to create an annual cost of care for the uninsured ACSC population with a PPH. I then multiplied this per person cost times the number of uninsured individuals with the corresponding PPH. The following equation depicts the anticipated aggregated incremental preventive care cost (AIPCC) for the uninsured in the state of Texas.

$$AIPCC = \sum_{i=1}^{7}\left(preventive\ care\ cost_{ACSC_i} * Uninsured\ in\ Texas_{ACSC_i}\right) - \left\{\left[\sum_{i=1}^{7} preventive\ care\ cost_{PPH_{ACSC_i}} * (Uninsured\ in\ Texas_{ACSC_i} - Uninsured\ in\ Texas_{PPH_{ACSC_i}})\right] + \left[\sum_{i=1}^{7}\left(\left(.5 * preventive\ care\ cost_{PPH_{ACSC_i}}\right) + followup\ care\ cost_{PPH_{ACSC_i}} + PPH\ Cost_{ACSC_i}\right) * Uninsured\ in\ Texas_{PPH_{ACSC_i}}\right]\right\}$$

Where

i = one of the seven ACSC conditions

preventive care cost$_{ACSC}$ = the adjusted annual preventive care cost estimated using the BCBSTX data for each ACSC

preventive care cost$_{PPHacsc}$ = the adjusted annual preventive care cost estimated using the BCBSTX data for each ACSC limited to beneficiaries with a PPH

followup $cost_{ACSC}$ = the adjusted six month healthcare cost estimated using the BCBSTX data for each ACSC after a PPH

PPH $cost_{ACSC}$ = the adjusted cost of the PPH associated with each ACSC

Uninsured in $Texas_{ACSC}$= the number of uninsured individuals estimated to have an ACSC in Texas

Uninsured in $Texas_{ACSCpph}$ = the number of uninsured individuals with an ACSC and a PPH in Texas

Next, I calculated the incremental cost of HAI in the uninsured PPH population. Using adjusted estimates of the incremental cost of HAI, I first added the incremental cost of HAI during hospitalization to the incremental cost of follow-up care for HAI. I then multiplied the sum of incremental costs by the number of PPH with each HAI. After summing across the four HAIs, I multiplied the estimated total incremental cost of HAI by the percentage of uninsured individuals in the PPH with HAI population. The following formula depicts the aggregated incremental HAI cost (AIHAIC):

$$AIHAIC = (\%\ of\ PPH\ with\ HAI\ that\ is\ uninsured) * \sum_{i=1}^{4} (number\ of\ PPH\ with\ HAI_i * (incremental\ cost\ of\ hospitalization\ for\ HAI_i + incremental\ cost\ of\ followup\ care\ for\ HAI_i))$$

Where

i = one of the four HAI conditions

Use of these two equations provided a maximum estimate of both costs assuming all the uninsured elected to participate in insurance and all PPH were preventable through preventive care. To determine how the estimate might fluctuate relative to uptake rates in the insurance market place or expansion of Medicaid under the ACA, I allowed the number of uninsured to fluctuate based on differing levels of uptake in the insurance market place translating to changes in the numbers of uninsured. To allow for the fact that insurance status may not translate directly to the number of individuals with PPH and HAI, I also allowed the percentage of uninsured with a PPH and HAI to fluctuate. The adjustments to insurance rates provided an opportunity to examine the sensitivity of costs related to preventive care, PPH and PPH with HAI.

CHAPTER V

RESULTS

Descriptive analyses

To meet the goals of specific aim one and because relatively little is known about the PPH with HAI population, the following descriptive analysis includes demographic descriptions and frequency of occurrence in the Texas inpatient and BCBSTX data. For the purposes of reporting descriptive analyses collectively and comparatively, the descriptive portion of specific aim three covering the BCBSTX PPH and ACSC populations' demographic and preventive care utilization is also included in this section.

Texas inpatient population, 2011

Demographics

Of the 2,937,134 discharges in the THCIC inpatient PUDF 2011 data, 202,511 (6.9%) were excluded for missing or invalid data in evaluation variables. Exclusions included 6 for missing age, 7,048 missing race, 190,529 for missing gender, 2,087 for missing principal diagnosis, 3,054 for missing primary payer, and 1,077 for length of stay greater than 180 days. Among the remaining 2,734,623 discharges, the AHRQ's PQI programs identified 179,797 (6.6%) as PPH. Using the methodologies described in the chapter four for identifying HAI, 16,274 (0.6%) of all discharges included evidence of an HAI. The number of individuals who acquired an HAI during a PPH admission was estimated at 1,034 (6.4% of PPH discharges).

Compared to the general 2011 Texas inpatient population, individuals with a PPH were older, with a noticeably higher proportion of patients using Medicare as their

primary insurer (Table 1). The proportion of males was greater in the PPH, HAI, and PPH with HAI populations when compared to the general inpatient population. However, all groups consisted of more females than males (Table 1). We observed a slightly greater proportion of Whites when comparing the inpatient population moving from total discharges to PPH to HAI to PPH with HAI (Table 1). Blacks demonstrated a higher proportion within the PPH population, while the Other race category had nearly double the proportion in the HAI population compared to the PPH, PPH with HAI and the general inpatient populations (Table 1). Another observation included a greater proportion of discharges with Medicare as primary payer of 54%, 59% and 64% for PPH, HAI admissions, and PPH with HAI admission respectively (Table 1). These proportions are higher than the general patient population with 34% of discharges with Medicare as primary payer (Table 1). All observed differences from the general inpatient population were statistically significant at a $p<.001$ level.

After exclusions, the final study population exhibited the same demographic characteristics with the exceptions of a larger proportion of the HAI population identifying Medicare as their primary payer (61% vs. 59%) (Table 2).

Table 1. Texas inpatients by PPH, HAI, PPH with HAI and general inpatient population for 2011, before exclusions.

	With PQI			With HAI			With Both			Total Discharges	
	N = 280,657		% of total	N = 16,274		% of total	N = 1,034		% of total	N = 2,935,047	
	n	%	discharges	n	%	discharges	n	%	discharges	n	%
Gender											
male	119,712	43%	4.08%	7,339	45%	0.25%	443	43%	0.02%	1,076,967	37%
missing	0	0%	0.00%	1,244	8%	0.04%	0	0%	0.00%	190,528	6%
Age Group											
under 1 Year	20,696	7%	0.71%	470	3%	0.02%	39	4%	0.00%	412,027	14%
1-17 Years	15,099	5%	0.51%	430	3%	0.01%	9	1%	0.00%	167,577	6%
18-24 Years	6,166	2%	0.21%	258	2%	0.01%	7	1%	0.00%	196,741	7%
25-44 Years	27,853	10%	0.95%	1,516	9%	0.05%	72	7%	0.00%	610,661	21%
45-64 Years	74,419	27%	2.54%	4,953	30%	0.17%	313	30%	0.01%	684,437	23%
65-74 Years	48,808	17%	1.66%	3,703	23%	0.13%	222	21%	0.01%	364,699	12%
75-84 Years	52,114	19%	1.78%	3,345	21%	0.11%	224	22%	0.01%	321,593	11%
85+ Years	35,502	13%	1.21%	1,599	10%	0.05%	148	14%	0.01%	177,306	6%
missing	0	0%	0.00%	0	0%	0.00%	0	0%	0.00%	6	0%
Race											
White	147,527	53%	5.03%	8,948	55%	0.30%	576	56%	0.02%	1,476,635	50%
Black	44,503	16%	1.52%	2,124	13%	0.07%	140	14%	0.00%	383,711	13%
Hispanic	71,416	25%	2.43%	3,479	21%	0.12%	258	25%	0.01%	840,708	29%
Asian/ Pacific Islander	2,804	1%	0.10%	224	1%	0.01%	10	1%	0.00%	48,357	2%
Amer. Indian./Eskimo/Aleut	2,235	1%	0.08%	63	0%	0.00%	7	1%	0.00%	20,858	1%
Other	11,351	4%	0.39%	1,347	8%	0.05%	42	4%	0.00%	157,756	5%
missing	821	0%	0.03%	89	1%	0.00%	1	0%	0.00%	7,022	0%
Primary Payer											
Private payer	57,827	21%	1.97%	3,337	21%	0.11%	155	15%	0.01%	927,566	32%
Medicare	151,025	54%	5.15%	9,673	59%	0.33%	681	66%	0.02%	992,145	34%
Medicaid	37,800	13%	1.29%	1,681	10%	0.06%	111	11%	0.00%	627,776	21%
Other Gov't	6,053	2%	0.21%	408	3%	0.01%	17	2%	0.00%	92,893	3%
Self-pay or Charity	27,882	10%	0.95%	1,114	7%	0.04%	69	7%	0.00%	291,172	10%
missing	6,056	2%	0.21%	61	0%	0.00%	1	0%	0.00%	3,495	0%

Source: Texas Healthcare Information Collection Inpatient Public Use Data File, 2011

Table 2. Texas inpatients by PPH, HAI, PPH with HAI and general inpatient population for 2011, after exclusions.

	With PPH			With HAI			With Both			Total Discharges	
	N = 279,767		% of total	N = 14,884		% of total	N = 1,031		% of total	N = 2,734,623	
	n	%	discharges	n	%	discharges	n	%	discharges	n	%
Gender											
Male	119,405	43%	4.37%	7,254	49%	0.27%	440	43%	0.02%	1,072,429	39%
Age Group											
under 1 Year	20,678	7%	0.76%	453	3%	0.02%	39	4%	0.00%	411,468	15%
1-17 Years	15,067	5%	0.55%	384	3%	0.01%	9	1%	0.00%	159,566	6%
18-24 Years	6,151	2%	0.22%	255	2%	0.01%	7	1%	0.00%	196,292	7%
25-44 Years	27,768	10%	1.02%	1,223	8%	0.04%	71	7%	0.00%	529,424	19%
45-64 Years	74,192	27%	2.71%	4,284	29%	0.16%	313	30%	0.01%	599,668	22%
65-74 Years	48,625	17%	1.78%	3,478	23%	0.13%	221	21%	0.01%	348,814	13%
75-84 Years	51,928	19%	1.90%	3,220	22%	0.12%	223	22%	0.01%	312,836	11%
85+ Years	35,358	13%	1.29%	1,587	11%	0.06%	148	14%	0.01%	176,555	6%
Race											
White	147,491	53%	5.39%	8,225	55%	0.30%	575	56%	0.02%	1,373,336	50%
Black	44,493	16%	1.63%	1,928	13%	0.07%	140	14%	0.01%	348,035	13%
Hispanic	71,404	26%	2.61%	3,198	21%	0.12%	258	25%	0.01%	798,534	29%
Asian/ Pacific Islander	2,804	1%	0.10%	218	1%	0.01%	10	1%	0.00%	47,414	2%
Amer. Indian./Eskimo/Aleut	2,230	1%	0.08%	59	0%	0.00%	6	1%	0.00%	19,918	1%
Other	11,345	4%	0.41%	1,256	8%	0.05%	42	4%	0.00%	147,386	5%
Primary Payer											
Private payer	57,543	21%	2.10%	3,038	20%	0.11%	155	15%	0.01%	874,094	32%
Medicare	150,554	54%	5.51%	9,192	62%	0.34%	679	66%	0.02%	940,666	34%
Medicaid	37,751	13%	1.38%	1,456	10%	0.05%	111	11%	0.00%	596,050	22%
Other Gov't	6,050	2%	0.22%	347	2%	0.01%	17	2%	0.00%	81,201	3%
Self-pay or Charity	27,869	10%	1.02%	851	6%	0.03%	69	7%	0.00%	242,612	9%

Source: Texas Healthcare Information Collection Inpatient Public Use Data File, 2011

THCIC PUDF inpatients identified as PPH with HAI

Because we are interested in the PPH with HAI population, and little is known about this group of individuals, I identified HAI across the PPH admissions (Table 3). When examining the PPH population, we observe the most frequently occurring PPHs are heart failure (HF), bacterial pneumonia (PN), and COPD or Asthma in adults with over 49, 43, and 41 thousand cases respectively. HF, PN, and COPD also accounted for the PPH with the most cases of an HAI, at 270,144, and 139 respectively (Table 3).

We also observed less than five HAI cases in almost all pediatric PPH admissions. Because of these limited cell counts, I elected to discontinue further evaluation of all of the pediatric PPHs due to the inability to draw meaningful statistical conclusions. Adult PPH excluded from further individual evaluation due to small case counts of HAI included hypertension, angina without procedure, uncontrolled diabetes, and asthma in younger adults. Based upon sample size calculations, PPH for low birth weight and dehydration were also excluded from further individualized analyses. The sample size necessary to detect a large effect in the presence of multi-covariates was estimated at over two million observations. Because individualized analyses of PPH were limited to the adult or pediatric population, logistic regression models were unlikely to estimate the maximum likelihood function reliably. Where cases existed for these PPH, the cases were included in evaluations that aggregated to an all PPH level of reporting.

Table 3. Frequency of HAIs in the PPH population for the state of Texas, 2011

PPH Type	CDI	SSI	CLABSI	CAUTI	VAP	PPH with HAI	PPH with No HAI	Total PPH
PQI01 Diabetes Short-Term Complications	21	0	4	2	4	31	10,991	11,022
PQI03 Diabetes Long-Term Complications	76	1	10	4	21	112	21,243	21,355
PQI05 COPD or Asthma in Older Adults	42	0	10	11	76	139	41,212	41,351
PQI07 Hypertension	3	0	2	2	1	8	10,925	10,933
PQI08 Heart Failure	104	0	24	44	98	270	49,496	49,766
PQI09 Low Birth Weight	2	0	29	0	5	36	17,904	17,940
PQI10 Dehydration	36	0	4	11	9	60	20,013	20,073
PQI11 Bacterial Pneumonia	97	0	26	13	8	144	43,424	43,568
PQI12 Urinary Tract Infection	96	0	14	17	8	135	34,708	34,843
PQI13 Angina without Procedure	1	0	0	0	0	1	1,954	1,955
PQI14 Uncontrolled Diabetes	2	0	0	0	0	2	3,030	3,032
PQI15 Asthma in Younger Adults	1	0	0	1	2	4	2,423	2,427
PQI16 Lower-Extremity Amputation among diabetes patients	46	0	4	4	23	77	3,620	3,697
PDI14 Asthma admission for under 18	1	0	1	0	0	2	7,560	7,562
PDI15 Diabetes (under 18)	0	0	0	0	0	0	1,275	1,275
PDI16 Gastroenteritis (under 18)	0	0	5	0	1	6	5,402	5,408
PDI18 Urinary Tract Infection (Under 18)	2	0	0	0	2	4	3,556	3,560
Subtotal	530	1	133	109	258	965	278,736	279,767
HAI with No PQI	6,381	389	1,353	940	4,789	13,454		
Total HAI	6,911	390	1,486	1,049	5,047	14,419		

Source: Texas Healthcare Information Collection Inpatient Public Use Data File, 2011 and AHRQ Quality Indicator programs

The HAI with the highest incidence in 2011 was CDI in both the PPH population and the overall inpatient population with 530 and 6,911 cases, respectively (Table 3). VAP demonstrated the second highest incidence at 258 and 5,047 cases for the PPH and overall inpatient populations, respectively (Table 3). Conversely, identification of SSI and CAUTI were limited due to inability to track the surgical population over a 90 day period, and lack of specificity in ICD-9-CM diagnosis codes for CAUTI. The inability to identify all cases of SSI translated to an inability to draw statistically meaningful individualized conclusions from analyses for SSI. However, where analyses aggregated to an all HAI level, cases of SSI were included.

Multiple PQI or HAI for one discharge

Because the methods for identifying PPH admissions and acquisition of HAI do not consider the presence of other PPH or HAIs, it was necessary to identify discharges with multiple PPH or HAI assignments. For the PPH, all 1,826 discharges identified with more than one PPH, identified PPH for diabetes related lower extremity amputation as one of the PPH. The secondary PPH was diabetes related for 1,814 of the 1,826 discharges. For the remaining discharges with multiple PPH assignments, the secondary PPH included heart failure (13), dehydration (2), urinary tract infection (2), and bacterial pneumonia (1). Because some analysis required mutually exclusive categories of PPH, the 1,814 PPH admissions with less severe forms of diabetic complications as a secondary PPH were assigned to diabetes related lower extremity amputation. For the remaining discharges, an unadjusted mean cost per discharge was used as a proxy for intensity of utilization. Since the unadjusted mean cost per discharge was highest for diabetes related lower extremity amputation, the remaining individuals with multiple PPH were also assigned to the diabetes related lower extremity amputation PPH for analyses requiring a mutually exclusive category.

For the HAIs, 496 discharges included multiple HAI. Of the 496 discharges with multiple HAIs, 235 were cases of both CDI and VAP, 82 cases with both VAP and CLABSI, 55 cases with both CDI and CAUTI, 57 cases with CDI and CAUTI, 40 cases of CAUTI and VAP, and 14 cases with CAUTI and CLABSI. Using unadjusted mean cost per discharge as a proxy for intensity of utilization, all discharges with multiple HAI were assigned to the highest intensity category of identified HAI for analyses that

required mutually exclusive categories. From highest intensity to lowest, the HAI categories were VAP, CLABSI, SSI, CDI and CAUTI.

BCBSTX populations

Datasets

Since the 2011 Texas pediatric inpatient population had extremely limited number of HAIs in the pediatric PPH population, only claims for patients 18 years of age and older were examined from the BCBSTX data. The data pull consisted of four populations within the BCBSTX claims data: beneficiaries with a hospital admission in 2011, beneficiaries with no hospital admission for 2011 with an ACSC, beneficiaries with a prenatal care diagnosis, and prescriptions for the included beneficiaries. Due to incomplete utilization information for managed care beneficiaries, 30,539 BCBSTX beneficiaries' information was not included. For 1,014,905 beneficiaries participating in a preferred provider payment structure, the BCBSTX data included over 38.7 million claim lines representing all types of utilization for individuals with a hospitalization in 2011. For beneficiaries with no hospitalization in 2011, 70.2 million claim lines represented all types of utilization for 788,091 beneficiaries with a potential ACSC. For beneficiaries with prescription drug coverage, approximately 23.2 million claim lines represented 327 thousand prescriptions for 574 thousand beneficiaries. Finally, nearly 8.5 million claim lines represented utilization for more than 735 thousand women with prenatal care.

BCBSTX inpatient PPH and HAI identification

For the beneficiaries that generated 156,296 inpatient stays in 2011, the AHRQ PQI software identified 9,783 inpatient discharges for 7,982 beneficiaries (Table 4). For the purposes of comparability to the PUDF, the BCBSTX demographic summary of inpatient stays is reported by number of discharges. Since all evaluation variables were populated with valid values, the only exclusions for the data centered on outlier length of stay where 8 inpatient stays exceeded 180 days.

Relative to the general BCBSTX inpatient population, individuals with a PPH were more likely to be female and slightly older (Table 4). When examined by HAI, individuals were more likely to be females aged 45 to 64 years than the general BCBSTX population (Table 4). We observed the same trend of slightly older females when comparing individuals admitted for a PPH with an HAI to the general BCBSTX inpatient population (Table 4). Consistently, approximately 90% of inpatient discharges where associated with the BCBS PPO plan verses the PPO+ plan (Table 4).

Compared to the THCIC PUDF Texas inpatient population, the BCBSTX inpatient population exhibited a slightly larger proportion of females (64.8%) with the bulk of beneficiaries (84.4%) between 25 and 64 years of age (Table 4). Although the BCBSTX proportion of females was larger, the Texas PUDF inpatient population by gender was comparable where 61% of discharges were female. However, the distribution by age was flatter in the THCIC PUDF, with approximately 41% of the general inpatient population between 25 and 64 years of age (Table 4).

Table 4. BCBSTX population by PPH, HAI, PPH with HAI and general inpatient population for 2011.

	With PQI			With HAI			With Both			Total Discharges	
	N= 9,783		% of total	N= 1,326		% of total	N= 67		% of total	N= 156,295	
	n	%	discharges	n	%	discharges	n	%	discharges	n	%
Gender											
male	4,292	43.9%	2.75%	703	53.0%	0.45%	33	49.3%	0.02%	55,003	35.19%
Age Group											
18-24 Years	528	5.4%	0.34%	63	4.8%	0.04%	2	3.0%	0.00%	14,109	9.03%
25-44 Years	2,267	23.2%	1.45%	263	19.8%	0.17%	12	17.9%	0.01%	62,474	39.97%
45-64 Years	5,694	58.2%	3.64%	792	59.7%	0.51%	38	56.7%	0.02%	68,836	44.04%
65-74 Years	764	7.8%	0.49%	123	9.3%	0.08%	7	10.4%	0.00%	7,575	4.85%
75-84 Years	442	4.5%	0.28%	73	5.5%	0.05%	7	10.4%	0.00%	2,900	1.86%
85+ Years	88	0.9%	0.06%	12	0.9%	0.01%	1	1.5%	0.00%	401	0.26%
Program Type											
PPO	8,776	89.7%	5.61%	1,208	91.1%	0.77%	58	86.6%	0.04%	140,969	90.19%
PPO+	1,007	10.3%	0.64%	118	8.9%	0.08%	9	13.4%	0.01%	15,326	9.81%

Source: Blue Cross/Blue Shield of Texas Claims data, 2011 and AHRQ Quality Indicator programs

Distribution of PPH with HAI within the BCBSTX population

To understand the effect of insurance on individuals admitted with a PPH, HAI, or PPH with HAI, I examined the distribution of admissions with HAI by type of PPH (Table 5). Overall, the BCBSTX population had fewer PPH admissions at 6.3% of total inpatient admissions verses the general Texas inpatient population at 9.5% of total admissions. For the BCBSTX population, bacterial pneumonia, hypertension, and dehydration were the most likely reasons for a PPH (Table 5). Like the THCIC PUDF Texas inpatient population, the methods used for identification for SSI demonstrated our limited ability to identify all SSI from unlinked discharge data and diagnosis codes (Table 5). Also important to note, due to lack of present on admission and procedure date information, modifications to the methods for identifying CDI and VAP likely overestimated the occurrence of these HAI events.

Table 5. Frequency of HAIs in the BCBSTX population with PPH, 2011

PPH Type	CDI	SSI	CLABSI	CAUTI	VAP	PPH with HAI	PPH with No HAI	Total PPH
PQI01 Diabetes Short-Term Complications	1	0	0	1	2	4	661	665
PQI03 Diabetes Long-Term Complications	5	0	1	1	1	8	966	974
PQI05 COPD or Asthma in Older Adults	5	0	0	0	9	14	1,346	1,360
PQI07 Hypertension	0	0	0	0	1	1	613	614
PQI08 Heart Failure	5	0	0	0	4	9	1,078	1,087
PQI10 Dehydration	3	0	0	2	2	7	1,276	1,283
PQI11 Bacterial Pneumonia	6	0	0	4	6	16	1,923	1,939
PQI12 Urinary Tract Infection	6	0	1	0	0	7	1,249	1,256
PQI13 Angina without Procedure	0	0	0	0	0	0	167	167
PQI14 Uncontrolled Diabetes	1	0	0	0	0	1	165	166
PQI15 Asthma in Younger Adults	0	0	0	0	0	0	194	194
PQI16 Lower-Extremity Amputation among diabetes patients	0	0	0	0	0	0	78	78
Subtotal	32	0	2	8	25	67	9,718	9,783
HAI with No PQI	438	41	46	100	633	1,258		
Total HAI	470	41	48	108	658	1,325		

Source: Blue Cross/Blue Shield of Texas Claims data, 2011 and AHRQ Quality Indicator programs

BCBSTX ambulatory care sensitive condition population, 2011

Of the 788,091 beneficiaries in the non-hospitalized data, 606,138 experienced utilization for an ACSC in 2011. The ACSC population followed similar demographic patterns to the hospitalized patient population for BCBSTX beneficiaries (Table 6). Of the 606,138 beneficiaries identified with an ACSC in 2011, the most prevalent conditions were hypertension, diabetes and urinary tract infection with 64.2%, 24.1%, and 19.5% of the ACSC population respectively. Just over 172 thousand beneficiaries experienced more than one ACSC in 2011. During analyses, other ACSC were treated as comorbid conditions.

Table 6. ACSC population demographics and ACSC, 2011

	n = 606,138	
	n	%
Gender		
male	247,700	40.9%
Age Group		
18-24 Years	30,858	5.1%
25-44 Years	193,508	31.9%
45-64 Years	344,795	56.9%
65-74 Years	29,340	4.8%
75-84 Years	6,845	1.1%
85+ Years	792	0.1%
Program Type		
PPO	8,776	1.4%
PPO+	1,007	0.2%
ACSC		
Diabetes	146,191	24.1%
COPD	40,728	6.7%
Hypertension	389,409	64.2%
Congestive Heart Failure	8,034	1.3%
Prenatal Care	50,198	8.3%
Dehydration	22,529	3.7%
Bacterial Pneumonia	11,872	2.0%
UTI	118,092	19.5%
Asthma	14,057	2.3%
Angina	9,967	1.6%

Source: Blue Cross/Blue Shield of Texas Claims data, 2011

For the 606,138 ACSC beneficiaries not hospitalized in 2011, utilization included nearly 7.3 million office visits, over 10 thousand home health visits, over 738 thousand outpatient visits, 197 emergency room visits, and more than 6.4 million prescriptions (Table 7). More than half of BCBSTX ACSC population included individuals with hypertension, multiple ACSC, and UTI (Table 7). However, prenatal care exhibited the highest mean number of office visits followed by individuals with multiple ACSC and CHF with 16.4, 14.9, and 14.1 office visits per year, respectively. Congestive Heart Failure led mean home healthcare services utilization with 22.3 home visits per year, followed by beneficiaries with dehydration and asthma using 16.1 and

Table 7. Utilization of healthcare services by ACSC population, 2011

	Office visits			Home Health Visits			Outpatient Care			Emergency Room visits			Prescriptions		
	n	Mean	S.D.	n	Mean	S.D.	n	Mean	S.D.	n	Mean	S.D.	n	Mean	S.D.
ACSC															
Diabetes	38,937	9.3	9.6	47	9.4	12.2	15,238	2.2	2.4	4	1.0	0.0	20,960	18.9	18.4
COPD	18,298	10.3	11.2	19	10.7	11.6	8,604	2.3	2.3	3	2.0	1.7	10,939	15.3	17.2
Hypertension	240,618	10.0	10.3	263	8.6	14.1	107,245	2.3	2.4	59	1.3	0.7	129,575	19.8	18.1
Congestive Heart Failure	1,074	14.1	13.7	3	22.3	30.9	645	3.1	4.4	0	-	-	578	25.8	23.5
Prenatal Care	50,198	16.4	9.6	182	7.2	7.7	28,971	2.8	2.9	0	-	-	26,751	13.1	13.8
Dehydration	12,197	10.7	13.3	16	16.1	28.3	6,570	2.2	2.4	3	1.3	0.6	6,960	11.9	14.5
Bacterial Pneumonia	5,488	10.1	10.4	10	9.3	8.6	2,627	2.3	3.0	1	1.0		3,180	12.8	14.5
UTI	70,195	11.7	11.2	55	12.7	25.5	34,002	2.2	2.1	5	1.4	0.9	39,696	13.7	14.8
Asthma	7,195	11.3	12.8	3	13.3	19.7	3,118	2.1	2.3	0	-	-	4,054	16.3	17.1
Angina	1,837	13.0	11.7	0	-	-	1,229	2.5	2.4	0	-	-	970	16.4	17.9
Multiple ACSC	160,101	14.9	13.6	388	12.3	22.3	89,344	2.8	3.3	66	1.5	0.8	83,086	30.2	25.2

Source: Blue Cross/Blue Shield of Texas Claims data, 2011

13.3 home visits per year, respectively (Table 7). Beneficiaries with CHF also led outpatient services mean utilization with 3.1 visits per year (Table 7). The BCBSTX ACSC population also exhibited minimal use of emergency room services (Table 7). Not unexpected, beneficiaries with multiple ACSC utilized prescription services a mean of 30.2 times per year, followed by beneficiaries with CHF at 25.8 prescription claims per year (Table7).

Bivariate and multivariate analyses

In this section of the results, I report the results of necessary bivariate analysis that support the proposed multivariate analyses. Also reported here are the odds ratios that conclude the analyses to fulfill the goals of specific aim one. The odds ratio analysis also includes the odds of acquiring an HAI by payer. These comparisons are included in partial fulfillment of the goals for specific aim four.

Texas inpatient population, 2011

Bivariate

To determine whether correlations existed between analyses variables, I examined a SAS® generated correlation matrix populated with Pearson correlation coefficients. The correlation p-values demonstrated that most associations were significant at a $p<.05$ level. Defining mildly correlated as a Pearson correlation coefficient with an absolute value between 0 and 0.3, and a moderate correlation as an absolute value between 0.31 and 0.7, only seven correlation coefficients were significant and large enough to be considered moderately strong. Four of the variables with moderately strong coefficients' were correlated with age, specifically room type (private,

semi-private or ward), primary payer, hypertension, and health status measured as the number of comorbid conditions (Pearson correlation coefficients -0.38, -0.43, 0.54, and 0.56, respectively). The other moderately strong associations were between primary payer and health status (-0.31), hypertension and diabetes mellitus (0.35), and hypertension and renal failure (0.31). No coefficients presented a strong association.

After evaluating the cost data for the presence of zero costs, generalized linear modeling quantified the effects of evaluation variables on cost of healthcare. All models demonstrated significant ability to measure variation in cost based upon the independent variable as measured by the *F*-statistic ($p<.001$). Of the PPH and comorbid conditions evaluated, all demonstrated significant relationships ($p<.05$) with cost except the diabetes-related lower extremity amputation PPH and several comorbid conditions. Comorbid conditions not significantly related to cost included valvular disease, pulmonary circulation disorders, renal failure, chronic peptic ulcer disease, lymphoma, metastatic cancer, solid tumor with metastases, and fluid and electrolyte disorders.

Using a similar approach, I used logistic regression to measure the association between the probability of acquiring an HAI and independent variables. All models converged, and I assessed multiple measures of model fit to understand the reliability of reported associations. While all models converged and most relationships were significant, there were several notable exceptions. For example, when comparing variables to reflect size of hospital, average daily census was significant while number of beds was not. Therefore, I selected average daily census as the best reflection of hospital size. In examining room type, a semi-private room was significantly different from a

ward, but a private room was not. For types of PPH, only long-term diabetes was not significantly associated with the probability of an HAI. For comorbid conditions, chronic peptic ulcer disease and depression did not demonstrate significant associations.

Odds of PPH with HAI

To achieve a better understanding of the associations between PPH and HAI, I examined whether individuals with a PPH were more likely than the general inpatient population to acquire an HAI during their hospital stay through odds ratios. Adjusted odds ratios reflect considerations for demographic characteristics, health status, hospital characteristics, and community characteristics as described in Chapter IV-Methods. Regression models evaluating the THIC PUDF data included 51 covariates. This left at least 1,854,861 degrees of freedom in each model.

With the exception of short-term diabetes, long-term diabetes and diabetes associated lower extremity amputation; individuals were significantly less likely to acquire CDI than the rest of the general inpatient population (Table 8). When compared to the overall PPH population, the odds of acquiring CDI by the general inpatient population was nearly 2 times the odds of the PPH population acquiring CDI (OR: .54, $CI_{95\%}$ .49, .59). While the short-term and long-term diabetes PPH did not demonstrate significant odds ratios for acquiring a CDI, the diabetes associated lower extremity amputation did (Table 8). In fact, the odds ratios reflect an effect of that individuals admitted with a diabetes related lower extremity amputation PPH had nearly three times

Table 8. Odds ratios of acquiring CDI by PPH type and payer, adjusted for demographic, health status, hospital, and community characteristics.

	PPH Denominator Population	CDI within Denominator Population	PPH with HAI	Odds Ratio	LCL	UCL
For all PPH	2,642,681	6,617	530	**0.54**	0.49	0.59
by PPH						
PQI01 Diabetes Short-Term Complications	1,862,070	5,919	21	1.12	0.73	1.73
PQI03 Diabetes Long-Term Complications	1,872,221	5,970	76	0.97	0.76	1.22
PQI05 COPD or Asthma in Older Adults	1,891,645	5,939	42	**0.24**	0.18	0.33
PQI08 Heart Failure	1,899,828	5,997	104	**0.50**	0.41	0.61
PQI10 Dehydration	1,870,759	5,933	36	**0.50**	0.36	0.70
PQI11 Bacterial Pneumonia	1,893,646	5,994	97	**0.57**	0.46	0.70
PQI12 Urinary Tract Infection	1,885,483	5,992	96	**0.61**	0.49	0.74
PQI16 Lower-Extremity Amputation among diabetes patients	1,854,910	5,945	46	**2.90**	2.16	3.91
All PPH by payer						
Medicare	2,642,681	6,617	530	**Referent**		
Private Insurance				**0.56**	0.52	0.61
Medicaid				**0.58**	0.51	0.66
Other				**0.53**	0.43	0.64
Self-Pay or Charity				**0.46**	0.40	0.53

Odds ratios in bold are significant at a p<.05 level

Source: Texas Healthcare Information Collection Inpatient Public Use Data File, 2011 and AHRQ Quality Indicator programs

Notes: Where not listed, the referent group is the non-PPH adult Texas inpatient population

the odds of acquiring CDI as the general inpatient population (OR: 2.9, $CI_{95\%}$ 2.16, 3.91)(Table 8). When examined by payer, accounting for the effects of PPH and HAI, the odds of the Medicare population acquiring CDI was approximately twice the odds of any other payer (Table 8). All payer categories contributed significantly to explain variation in the probability of acquiring a CDI infection (Table 8).

When examining CLABSI and PPH, individuals admitted for a PPH were less likely to acquire CLABSI than the general inpatient population, except for the diabetes related lower extremity amputation PPH. Effects ranged from an odds ratio of .37 for dehydration to 1.65 for diabetes related lower extremity amputation (Table 9). PPH considered significant in explaining variation in the probability of acquiring CLABSI

Table 9. Odds ratios of acquiring CLABSI by PPH type and payer, adjusted for demographic, health status, hospital, and community characteristics.

	PPH Denominator Population	CLABSI within Denominator Population	PPH with HAI	Odds Ratio	LCL	UCL
For all PPH	2,642,681	1,532	133	**0.729**	0.609	0.874
by PPH						
PQI01 Diabetes Short-Term Complications	1,862,070	1120	4	0.683	0.255	1.830
PQI03 Diabetes Long-Term Complications	1,872,221	1125	10	0.618	0.320	1.196
PQI05 COPD or Asthma in Older Adults	1,891,645	1127	10	**0.387**	0.213	0.703
PQI08 Heart Failure	1,899,828	1141	24	0.847	0.566	1.267
PQI10 Dehydration	1,870,759	1120	4	**0.366**	0.137	0.977
PQI11 Bacterial Pneumonia	1,893,646	1142	26	0.889	0.600	1.317
PQI12 Urinary Tract Infection	1,885,483	1129	14	**0.514**	0.296	0.892
PQI16 Lower-Extremity Amputation among diabetes patients	1,854,910	1121	4	1.654	0.679	4.031
All PPH by payer						
Medicare	2,642,681	1,532	133	**Referent**		
Private Insurance				**0.734**	0.618	0.872
Medicaid				**1.163**	0.953	1.418
Other				0.892	0.643	1.238
Self-Pay or Charity				**0.742**	0.583	0.945

Odds ratios in bold are significant at a p<.05 level

Source: Texas Healthcare Information Collection Inpatient Public Use Data File, 2011 and AHRQ Quality Indicator programs

Notes: Where not listed, the referent group is the non-PPH adult Texas inpatient population

included dehydration, COPD, and UTI where odds ratios were .37, .39, and .51 respectively (Table 9). Additionally, dehydration, COPD, and UTI demonstrated the largest effects (Table 9). While differences among payers were significant, the measurable effect was considered moderate (Table 9).

When examining the odds of acquiring CAUTI, we observed the general inpatient population had significant odds of acquiring CAUTI that were approximately 2.5 times the odds of individuals admitted with a COPD/asthma PPH (OR: .40, $CI_{95\%}$ .23, .71) or individuals admitted for the bacterial pneumonia PPH (OR: .43, $CI_{95\%}$ .25, .75)(Table 10). The largest adverse odds ratio was for the diabetes related lower extremity amputation PPH where patients admitted for diabetes related lower extremity

amputation had an odds of acquiring CAUTI that was 2.3 times that of the general inpatient population, however the relationship was not considered significant. When we compared PPH patients with the general inpatient population, we observed significantly lower odds of acquiring CAUTI by the PPH population approximately two thirds that of the general inpatient population. We observed a relationship of similar magnitude and significance between Medicare and privately insured individuals where Medicare beneficiaries odds of acquiring CAUTI were 1.5 times that of privately insured patients.

Table 10. Odds ratios of acquiring CAUTI by PPH type and payer, adjusted for demographic, health status, hospital, and community characteristics.

	PPH Denominator Population	CAUTI within Denominator Population	PPH with HAI	Odds Ratio	LCL	UCL
For all PPH	2,636,064	1,118	109	**0.677**	0.556	0.826
by PPH						
PQI01 Diabetes Short-Term Complications	1,862,070	997	2	0.657	0.163	2.640
PQI03 Diabetes Long-Term Complications	1,872,221	1,000	4	0.438	0.181	1.058
PQI05 COPD or Asthma in Older Adults	1,891,645	1,007	11	**0.402**	0.227	0.713
PQI08 Heart Failure	1,899,828	1,039	44	1.281	0.940	1.747
PQI10 Dehydration	1,870,759	1,006	11	0.887	0.488	1.610
PQI11 Bacterial Pneumonia	1,893,646	1,008	13	**0.431**	0.249	0.748
PQI12 Urinary Tract Infection	1,885,483	1,012	17	0.622	0.383	1.009
PQI16 Lower-Extremity Amputation among diabetes patients	1,854,910	1,000	4	2.301	0.944	5.606
All PPH by payer						
Medicare	2,636,064	1,118	109	**Referent**		
Private Insurance				**0.666**	0.541	0.82
Medicaid				0.897	0.666	1.208
Other				0.772	0.494	1.204
Self-Pay or Charity				0.828	0.614	1.118

Odds ratios in bold are significant at a p<.05 level

Source: Texas Healthcare Information Collection Inpatient Public Use Data File, 2011 and AHRQ Quality Indicator programs

Notes: Where not listed, the referent group is the non-PPH adult Texas inpatient population

For VAP, associations with all PPH were significant and size of effect was large (Table 11). With the exception of lower extremity amputation, all other PPH

demonstrated that patients with a PPH were less likely to acquire an HAI with odds ratios ranging from .056 to .56 (Table 11). However, the odds of acquiring VAP for individuals admitted with diabetes related lower extremity amputation were 1.44 times that of the general inpatient population (Table 11). By payer, private insurance and Medicaid were significantly different from Medicare, but the size of the effect was small (Table 11).

Table 11. Odds ratios of acquiring VAP by PPH type and payer, adjusted for demographic, health status, hospital, and community characteristics.

	PPH Denominator Population	VAP within Denominator Population	PPH with HAI	Odds Ratio	LCL	UCL
For all PPH	2,642,681	5,012	258	**0.34**	0.30	0.38
by PPH						
PQI01 Diabetes Short-Term Complications	1,862,070	4492	4	**0.20**	0.07	0.53
PQI03 Diabetes Long-Term Complications	1,872,221	4509	21	**0.31**	0.20	0.48
PQI05 COPD or Asthma in Older Adults	1,891,645	4560	76	**0.56**	0.45	0.71
PQI08 Heart Failure	1,899,828	4580	98	**0.56**	0.46	0.70
PQI10 Dehydration	1,870,759	4497	9	**0.19**	0.10	0.37
PQI11 Bacterial Pneumonia	1,893,646	4496	8	**0.06**	0.03	0.11
PQI12 Urinary Tract Infection	1,885,483	4496	8	**0.08**	0.04	0.17
PQI16 Lower-Extremity Amputation among diabetes patients	1,854,910	4511	23	**1.44**	0.95	2.18
All PPH by payer						
Medicare	2,642,681	5,012	258	**Referent**		
Private Insurance				**0.77**	0.70	0.84
Medicaid				**1.11**	0.99	1.25
Other				1.06	0.89	1.26
Self-Pay or Charity				1.00	0.88	1.13

Odds ratios in bold are significant at a p<.05 level

Source: Texas Healthcare Information Collection Inpatient Public Use Data File, 2011 and AHRQ Quality Indicator programs

Notes: Where not listed, the referent group is the non-PPH adult Texas inpatient population

BCBSTX populations, 2011

Bivariate

To examine associations between evaluation variables in the BCBXTX data, I used SAS® 9.3 to generate a correlation matrix, and used Pearson correlation coefficients to quantify associations. While approximately half of the variable combinations exhibited significant associations, only two exhibited a moderately strong association. Similar to the THCIC inpatient population, age was significantly and moderately associated with hypertension and health status as measured by the number of comorbid conditions. Pearson correlation coefficients were both .44 and significant at a p=<.001 level. All other associations reflected a weak association regardless of significance.

For examining evaluation variables in association with the probability of acquiring an HAI during hospitalization, I used logistic regression. All models converged, and I assessed multiple measures of model fit to understand the reliability of reported associations. Of the evaluation variables, none of the PPH variables were significantly associated in predicting the acquisition of an HAI. Variables considered significant in bivariate logistic regression of the probability of acquiring an HAI were age, gender, and health status as measured by the number of comorbid conditions. Individual comorbid conditions considered significant were CHF, pulmonary circulation disorders, hypertension, paralysis, neurological disorders, chronic pulmonary lung diseases, diabetes without complications, hypothyroidism, renal failure, liver disease, lymphoma, metastatic cancers, non-metastatic tumors, coagulation disorders, weight

loss, dehydration, alcohol abuse, and depression. All relationships were significant at a $p<.05$ level.

Odds of PPH with HAI in the BCBSTX hospitalized population

To examine associations between PPH and acquisition of an HAI during hospitalization for the BCBSTX population, I used SAS® 9.3 to calculate odds ratios while adjusting for age, gender, and comorbid conditions. Consistent with the bivariate analyses, we observed no significant associations between the PPH and CDI. We observed significant associations between VAP and long-term diabetes, bacterial pneumonia, and the all PHH variables (Table 12). Additionally, the odds ratios suggest that the general BCBSTX inpatient population is more than 14 times as likely to acquire an HAI as the long-term diabetes PPH beneficiary, and approximately 2.5 times as likely as a pneumonia PPH beneficiary or anyone admitted with a PPH (Table 12). Similar effect sizes are exhibited between VAP and the dehydration PPH, VAP and the short-term diabetes PPH, and the short-term diabetes PPH and CDI, but these associations were not significant (Table 12).

Table 12. Odds ratios of acquiring an HAI by type of PPH in the BCBSTX inpatient population, 2011

		CDI					VAP				
	PPH Denominator Population	CDI Population	PPH with CDI	Odds Ratio	LCL	UCL	VAP Population	PPH with VAP	Odds Ratio	LCL	UCL
For all PPH	156,287	486	32	0.78	0.54	1.12	658	25	**0.41**	0.27	0.61
by PPH											
PQI01 Diabetes Short-Term Complications	147,169	455	1	0.33	0.05	2.35	635	2	0.48	0.12	1.95
PQI03 Diabetes Long-Term Complications	147,478	459	5	1.09	0.45	2.69	634	1	**0.14**	0.02	0.98
PQI05 COPD or Asthma in Older Adults	147,864	459	5	1.04	0.43	2.55	642	9	1.32	0.67	2.60
PQI08 Heart Failure	147,591	459	5	0.96	0.39	2.37	637	4	0.61	0.23	1.66
PQI10 Dehydration	147,787	457	3	0.71	0.23	2.21	635	2	0.38	0.09	1.53
PQI11 Bacterial Pneumonia	148,443	460	6	0.70	0.31	1.59	639	6	**0.40**	0.17	0.90
PQI12 Urinary Tract Infection	147,760	460	6	1.08	0.48	2.45	143	0			
PQI16 Lower-Extremity Amputation among diabetes patients	146,582	454	0				207	0			

Odds ratios in bold are significant at a p<.05 level

Source: Blue Cross/Blue Shield of Texas Claims data, 2011 and AHRQ Quality Indicator programs

Note: Adjusted for age, gender, and comorbid conditions. Where not listed, the referent group is the non-PPH adult BCBSTX inpatient population

Cost of care

In this final section of the results, I report the multivariate evaluation of costs for the THCIC inpatient PUDF and the BCBSTX data. The results of the THCIC inpatient PUDF cost analysis fulfills the goals of specific aim two, while the costs of preventive care and follow-up generated from the BCBSTX data allows the fulfillment the goals of specific aim three, and to generate an answer to the hypothesis question. Included in the THCIC inpatient PUDF multivariate analysis of cost and throughout generation of an answer to the hypothesis question is an evaluation by payer, fulfilling the goals of specific aim four.

Texas inpatient population, 2011

In examining costs, I adjusted for demographic, health status, hospital and community characteristics and limited the regression populations to adults. Additionally, all cost models were considered significant as measured by the *F*-statistic ($p<.0001$). Models contained 790 to 792 covariates depending upon the number of DRGs in the denominator population, leaving a minimum of 1,854,118 degrees of freedom for any of the cost regression models. After adjustment, the differences in mean hospitalization cost attributable to PPH were approximately $2,100 less than other hospitalizations (Tables 13-17). One exception included hospitalizations for heart failure at approximately $425 more per admission when compared to the mean cost of hospitalization for the remaining inpatient population (Tables 13-17). Surprisingly, admissions for diabetes related lower extremity amputation were approximately $4,100 per admission less than other inpatient stays after adjustment (Tables 13-17). We also observed that when private insurance was

listed as primary payer, hospitalizations costs range from $2,050 more per person than Medicaid to $3,994 more per person than the uninsured (Tables 13-17).

Table 13. Mean differences in cost of inpatient care for CDI by PPH, 2011

	n	Mean difference due to PPH[1]	S.E.	Mean difference due to HAI[2]	S.E.
For all PPH	2,642,681	-$2,102	$64	$17,040	$240
by PPH					
PQI01 Diabetes Short-Term Complications	1,862,070	-$5,349	$457	$17,028	$272
PQI03 Diabetes Long-Term Complications	1,872,221	-$2,309	$226	$17,042	$271
PQI05 COPD or Asthma in Older Adults	1,891,645	-$2,104	$195	$17,071	$270
PQI08 Heart Failure	1,899,828	$461	$202	$16,931	$268
PQI10 Dehydration	1,870,759	-$596	$171	$16,968	$271
PQI11 Bacterial Pneumonia	1,893,646	-$1,867	$208	$16,934	$269
PQI12 Urinary Tract Infection	1,885,483	-$1,170	$283	$16,880	$269
PQI16 Lower-Extremity Amputation among diabetes patients	1,854,910	-$4,119	$503	$16,985	$272
All PPH by payer and adjusting for CDI					
Private Insurance	2,642,681	**Referent**			
Medicare		-$2,257	$40		
Medicaid		-$2,052	$37		
Other Gov't		-$2,964	$74		
Self-Pay or Charity		-$3,987	$47		

All associations are significant at a p<.01 level.
Source: Texas Healthcare Information Collection Inpatient Public Use Data File, 2011 and AHRQ Quality Indicator programs
Note: All differences are adjusted for demographic, health status, community and hospital characteristics.
1. Difference in mean cost between the non-PPH adult Texas inpatient population and the specified PPH population
2. Difference in mean costs between the non-HAI adult Texas inpatient population and the Texas inpatient population

When examining the effect of CDI on cost, increased payments per admission were estimated at $17 thousand (Table 13). Where an admission was potentially preventable and CDI acquired by the patient, the increase in hospitalization costs was approximately $14,900 per admission.

Table 14. Mean differences in cost of inpatient care for CLABSI by PPH, 2011

	n	Mean difference due to PPH	S.E.	Mean difference due to HAI	S.E.
For all PPH	2,642,681	-$2,136	$64	$32,408	$498
by PPH					
PQI01 Diabetes Short-Term Complications	1,862,070	-$5,436	$458	$22,283	$623
PQI03 Diabetes Long-Term Complications	1,872,221	-$2,352	$226	$22,248	$621
PQI05 COPD or Asthma in Older Adults	1,891,645	-$2,155	$196	$22,348	$617
PQI08 Heart Failure	1,899,828	$462	$202	$22,181	$612
PQI10 Dehydration	1,870,759	-$604	$172	$22,241	$622
PQI11 Bacterial Pneumonia	1,893,646	-$1,974	$208	$22,215	$613
PQI12 Urinary Tract Infection	1,885,483	-$1,298	$283	$22,155	$617
PQI16 Lower-Extremity Amputation among diabetes patients	1,854,910	-$4,086	$60	$22,367	$624
All PPH by payer adjusting for CLABSI					
Private Insurance	2,642,681	**Referent**			
Medicare		-$2,057	$40		
Medicaid		-$2,057	$37		
Other Gov't		-$2,969	$74		
Self-Pay or Charity		-$3,990	$47		

All associations are significant at a p<.01 level.
Source: Texas Healthcare Information Collection Inpatient Public Use Data File, 2011 and AHRQ Quality Indicator programs
Note: All differences are adjusted for demographic, health status, community and hospital characteristics.
1. Difference in mean cost between the non-PPH adult Texas inpatient population and the specified PPH population
2. Difference in mean costs between the non-HAI adult Texas inpatient population and the Texas inpatient population

When examining the effect of CLABSI on cost, we observed a difference in mean hospitalization cost of more than $32 thousand per hospitalization (Table 14). We also observed that none of the incremental CLABSI cost reported by type of PPH is more than $23 thousand dollars. This suggests that the effect of CLABSI in PPH such as hypertension, low birth weight babies, or pediatric gastroenteritis generates significant utilization driving the mean adjusted cost upward (Table 14). When a PPH admitted individual also acquired CLABSI, the incremental increase in the adjusted mean cost was approximately $30,100 per admission.

Table 15. Mean differences in cost of inpatient care for CAUTI by PPH, 2011

	n	Mean difference due to PPH	S.E.	Mean difference due to HAI	S.E.
For all PPH	2,642,681	-$2,132	$64	$13,118	$582
by PPH					
PQI01 Diabetes Short-Term Complications	1,862,070	-$5,438	$458	$13,300	$659
PQI03 Diabetes Long-Term Complications	1,872,221	-$2,350	$226	$13,414	$657
PQI05 COPD or Asthma in Older Adults	1,891,645	-$2,161	$196	$13,307	$651
PQI08 Heart Failure	1,899,828	$455	$202	$13,340	$640
PQI09 Low Birth Weight					
PQI11 Bacterial Pneumonia	1,893,646	-$1,953	$208	$13,272	$651
PQI12 Urinary Tract Infection	1,885,483	-$1,282	$283	$13,101	$651
PQI16 Lower-Extremity Amputation among diabetes patients	1,854,910	-$4,119	$503	$13,361	$660
All PQI by payer adjusting for CAUTI					
Private Insurance	2,642,681	**Referent**			
Medicare		-$2,239	$41		
Medicaid		-$2,050	$37		
Other Gov't		-$2,968	$74		
Self-Pay or Charity		-$3,994	$47		

All associations are significant at a p<.01 level.
Source: Texas Healthcare Information Collection Inpatient Public Use Data File, 2011 and AHRQ Quality Indicator programs
Note: All differences are adjusted for demographic, health status, community and hospital characteristics.
1. Difference in mean cost between the non-PPH adult Texas inpatient population and the specified PPH population
2. Difference in mean costs between the non-HAI adult Texas inpatient population and the Texas inpatient population

For CAUTI , we observed a mean increase of over $13 thousand per admission (Table 15). Depending on the type of PPH, the increased cost was offset by the mean difference related to a PPH admission. On average, the mean cost of CAUTI during a PPH admission was $11,000 more than the mean cost of the hospitalization for the non-PPH inpatient population in Texas.

Table 16. Mean differences in cost of inpatient care for VAP by PPH, 2011

	n	Mean difference due to PPH	S.E.	Mean difference due to HAI	S.E.
For all PPH	2,642,681	-$2,119	$64	$32,541	$286
by PPH					
PQI01 Diabetes Short-Term Complications	1,862,070	-$5,418	$457	$29,609	$325
PQI03 Diabetes Long-Term Complications	1,872,221	-$2,354	$226	$29,615	$324
PQI05 COPD or Asthma in Older Adults	1,891,645	-$2,245	$195	$29,360	$320
PQI08 Heart Failure	1,899,828	$395	$202	$29,519	$319
PQI10 Dehydration	1,870,759	-$601	$171	$29,584	$324
PQI11 Bacterial Pneumonia	1,893,646	-$1,818	$208	$29,610	$322
PQI12 Urinary Tract Infection	1,885,483	-$1,262	$283	$29,592	$323
PQI16 Lower-Extremity Amputation among diabetes patients	1,854,910	-$4,073	$325	$29,691	$325
All PPH by payer adjusting for VAP					
Private Insurance	2,642,681	**Referent**			
Medicare		-$2,237	$40		
Medicaid		-$2,057	$37		
Other Gov't		-$2,974	$74		
Self-Pay or Charity		-$3,994	$47		

All associations are significant at a p<.01 level.
Source: Texas Healthcare Information Collection Inpatient Public Use Data File, 2011 and AHRQ Quality Indicator programs
Note: All differences are adjusted for demographic, health status, community and hospital characteristics.
1. Difference in mean cost between the non-PPH adult Texas inpatient population and the specified PPH population
2. Difference in mean costs between the non-HAI adult Texas inpatient population and the Texas inpatient population

VAP exhibited the largest incremental increase in hospitalization cost at approximately $32,500 for all PPH (Table 16). Like the incremental cost of HAI for CLABSI, VAP incremental cost of HAI is larger for all PPH than for estimates limited to an individual PPH. Suggesting other PPH with VAP such a low birth weight babies, hypertension, asthma, or any of the pediatric PPH may generate substantial utilization and associated costs (Table 16).

Table 17. Mean differences in cost of inpatient care for all HAI by PPH, 2011

	n	Mean difference due to PPH	S.E.	Mean difference due to HAI	S.E.
For all PPH	2,642,681	-$2,082	$64	$23,559	$170
by PPH					
PQI01 Diabetes Short-Term Complications	1,862,070	-$5,305	$456	$21,266	$195
PQI03 Diabetes Long-Term Complications	1,872,221	-$2,289	$225	$21,268	$194
PQI05 COPD or Asthma in Older Adults	1,891,645	-$2,154	$195	$21,241	$193
PQI08 Heart Failure	1,899,828	$402	$202	$21,196	$192
PQI10 Dehydration	1,870,759	-$587	$171	$21,215	$195
PQI11 Bacterial Pneumonia	1,893,646	-$1,749	$207	$21,188	$193
PQI12 Urinary Tract Infection	1,885,483	-$1,120	$282	$21,145	$193
PQI16 Lower-Extremity Amputation among diabetes patients	1,854,910	-$4,061	$502	$21,279	$195
All PPH by payer adjusting for HAI					
Private Insurance	2,642,681	**Referent**			
Medicare		-$2,266	$40		
Medicaid		-$2,065	$40		
Other Gov't		-$2,967	$74		
Self-Pay or Charity		-$3,982	$47		

All associations are significant at a p<.01 level.
Source: Texas Healthcare Information Collection Inpatient Public Use Data File, 2011 and AHRQ Quality Indicator programs
Note: All differences are adjusted for demographic, health status, community and hospital characteristics.
1. Difference in mean cost between the non-PPH adult Texas inpatient population and the specified PPH population
2. Difference in mean costs between the non-HAI adult Texas inpatient population and the Texas inpatient population

Across all PPH and all HAI, the mean adjusted incremental cost of a PPH is less than other hospitalizations by approximately $2,000 (Table 17). However, when an HAI is acquired, the mean adjusted incremental cost of hospitalization increased by approximately $23,500 in 2011(Table 17). When a PPH and HAI occur during the same admission, the mean adjusted cost per hospitalization is approximately $21,500 more than the mean adjusted cost of other hospitalizations per hospitalization (Table 17).

BCBSTX cost of healthcare for beneficiaries with a PPH admission in 2011

To aggregate healthcare utilization for BCBSTX beneficiaries with a PPH during 2011, I used the PPH discharge date to assign other utilization as either pre or post PPH utilization. After adjusting for gender, age, and comorbid conditions, I elected to report findings by plan type since the foundation of my analyses is pinned to access through insurance. Differences in mean pre-PPH utilization costs by plan type were not found to be significant. Estimates for aggregated mean healthcare utilization occurring in the year prior to the PPH ranged from $29 thousand for heart failure to $288 thousand for diabetes related lower extremity amputation (Table 18). For the six months after the PPH, aggregated and adjusted healthcare utilization ranged from $27 thousand for heart failure beneficiaries to $291 thousand for diabetes related lower extremity amputation patients (Table 18). When examining post PPH healthcare costs, six-month follow-up costs were similar in magnitude to costs reported for annual pre-PPH utilization. Although differences in mean payment by plan type were not significant, the models estimating cost were considered significant at a $p<.001$ level as measured by the *F*-statistic. Regression models included 20 to 29 covariates to adjust for demographic and health status and varied depending upon the presence of comorbid conditions in the PPH population being measured.

When examining the effect of acquiring an HAI during a PPH on utilization of healthcare services after a PPH, significant increases in mean healthcare utilization attributable to HAI were associated with COPD or long-term complications of diabetes with increases of over $36 thousand and nearly $48 thousand, respectively. While post-

Table 18. Preventive care cost for BCBSTX beneficiaries before and after a PPH

	Pre-hospitalization				Post PPH				Post PPH with HAI		
	n	PPO Mean payment	PPO+ Mean payment	S.E.	n	PPO Mean payment	PPO+ Mean payment	S.E.	n	Mean HAI effect[1] on payment	S.E.
For all PPH									8,099	**$15,035**	$4,422
by PPH											
PQI01 Diabetes Short-Term Complications	477	$40,847	$38,134	$1,943	477	$42,797	$39,870	$1,912	477		
PQI03 Diabetes Long-Term Complications	742	$51,166	$58,852	$4,428	742	$42,440	$49,801	$4,417	742	**$47,952**	$15,226
PQI05 COPD or Asthma in Older Adults	1,106	$67,415	$68,905	$1,798	1,106	$63,140	$64,875	$1,760	1,106	**$36,264**	$7,967
PQI08 Heart Failure	829	$29,325	$26,685	$3,289	829	$27,079	$24,594	$3,269	829	$6,432	$12,375
PQI10 Dehydration	1,104	$78,338	$79,163	$2,905	1,104	$73,648	$74,245	$2,902	1,104	-$9,526	$13,644
PQI11 Bacterial Pneumonia	1,708	$85,935	$82,229	$2,605	1,708	$80,818	$77,363	$2,613	1,708	-$4,177	$10,161
PQI12 Urinary Tract Infection	1,088	$58,293	$57,286	$1,851	1,088	$56,707	$56,231	$1,833	1,088	$31,271	$10,765
PQI16 Lower-Extremity Amputation among diabetes patients	49	$288,150	$276,420	$37,270	49	$291,429	$277,744	$37,353	49		

Mean effects in bold are significant at a p<.001 for HAI

Source: Blue Cross/Blue Shield of Texas Claims data, 2011

NOTE: All estimates are adjusted for demographic characteristics and health status. Population includes adults from the BCBSTX with the described PPH in 2011.

1. Referent group are individuals with no HAI within the described PPH population.

PPH with HAI utilization for dehydration and bacterial pneumonia were on average $9,500 and $4,200 less than PPH individuals with no HAI, these differences were not considered significant. Additionally, although other PPH specific differences in mean post-PPH utilizations were not significant, the mean effect of HAI on post-PPH healthcare utilization was significant and increased post-PPH utilization costs by $15 thousand (Table 18).

BCBSTX ambulatory care sensitive condition population, 2011

For beneficiaries with no PPH and evidence of healthcare for an ACSC in 2011, aggregated healthcare utilization costs estimated annual utilization for each ACSC. After adjusting for age, gender and health status, all differences between payment plans were significant. Additionally, all models were deemed significant at a $p<.001$ level as measured by the *F*-statistic. All models contained 31 or 32 covariates depending upon the presence of comorbid conditions.

Mean adjusted annual payment for healthcare associated with an ACSC was highest for bacterial pneumonia followed by dehydration (Table 19). However, bacterial pneumonia accounted for less than 2% of individuals and dehydration accounted for less than 3%. Conversely, hypertension affected the most individuals in the BCBSTX population with nearly 390 thousand individuals (Table 19). While diabetes was the second most frequently occurring condition among the BCBSTX population, it accounted for 18% of the population at a mean annual cost of just over $110 thousand in preventive care.

Table 19. Mean annual payment for preventive care by ACSC

ACSC	n	PPO Mean payment	PPO+ Mean payment	S.E.
Diabetes	145,210	$110,139	$109,218	$205
COPD	40,418	$117,346	$113,521	$501
Hypertension	386,300	$112,752	$110,760	$141
Congestive Heart Failure	7,950	$112,548	$106,668	$1,270
Low Birth Weight/ Pre-Natal Care	50,198	$80,530	$81,361	$117
Dehydration	21,569	$142,056	$137,886	$1,414
Bacterial Pneumonia	11,739	$145,974	$143,407	$1,127
UTI	109,611	$124,073	$122,164	$339
Asthma	13,808	$76,795	$74,149	$799
Angina	9,949	$126,940	$120,184	$1,375

All difference are significant at a p<.05 for HAI
Source: Blue Cross/Blue Shield of Texas Claims data, 2011
NOTE: All estimates are adjusted for demographic characteristics and health status.

Calculation of statewide costs

Let us restate the hypothesis question here to remind us how the previously generated cost estimates were intended to be applied to answer the question. Hypothesis question: Following the full implementation of ACA, will the increase in preventive care cost attributable to improved insurance coverage for individuals with ACSCs be offset by reductions in costs associated a reduced rate of HAI during a PPH?

Hence, we must estimate the cost of preventive care for the uninsured ACSC population before and after attaining insurance to measure the increase in preventive care utilization. Then we must estimate the total incremental effect an HAI has on the PPH population during and after hospitalization by estimating the difference in costs between individuals with a PPH and individuals with a PPH with HAI.

Calculation of statewide preventive care cost

To estimate the preventive care costs for the ACSC population, we must estimate the number of the uninsured with ACSCs. Using prevalence rates reported by the Texas

Department of State Health Services or reported by the CDC for the seven ACSC remaining in the analyses, I estimated the number of uninsured with each ACSC. In combination with adjusted mean cost estimates generated previously (Table 18 and 19), I estimated annual costs for individuals using preventive care without a PPH and annual cost for individuals with a PPH (Table 20). Diabetes accounted for the most frequently occurring condition, while bacterial pneumonia accounted for the most expensive annual preventive care (Table 20). Bacterial pneumonia also generated the most cost for the PPH population per person with the largest per person differences between preventive care for heart failure and PPH care for heart failure. Additionally, only asthma is less expensive for preventive care than for PPH and follow-up care at the per person level (Table 20).

When aggregated to the state level, I observed that diabetes contributed the most to the aggregated difference between cost for preventive verses PPH patterns of utilization while bacterial pneumonia contributed the least. Estimated cost of healthcare for the PPH population accounted for the likelihood of a "non-preventable" PPH and the likelihood of acquiring an HAI (Table 20). The net increase in expenditures is estimated at $66.9 billion for approximately 1.3 million uninsured individuals (Table 20). If the net cost were dispersed across the entire uninsured population, the additional cost per person equates to approximately $11,100 per year per uninsured person for the ACSC included in Table 20.

Table 20. Calculations for increase in preventive healthcare costs for Texas

ACSC	Estimated number of uninsured with ACSC	Annual cost per person of preventive care for ACSC	Annual cost of preventive care in the BCBSTX population with a PPH	Six-month follow-up cost of healthcare after PPH	Cost of PPH	Total Annual Preventive Care Cost	Current annual cost of care for Uninsured with ACSC	Net Annual Increase to insure the Uninsured
Diabetes	425,552	$110,139	$52,196	$56,442	$12,921	$46,870,043,560	$22,224,523,443	$24,645,520,117
COPD	245,680	$117,346	$63,140	$68,905	$14,203	$28,829,525,756	$15,515,853,653	$13,313,672,103
Congestive Heart Failure	175,485	$112,548	$27,079	$29,325	$16,833	$19,750,595,243	$4,755,848,085	$14,994,747,158
Dehydration	88,280	$142,056	$78,338	$73,648	$15,627	$12,540,721,584	$6,922,130,495	$5,618,591,090
Bacterial Pneumonia	15,443	$145,974	$80,818	$60,325	$14,341	$2,254,236,909	$1,254,920,736	$999,316,174
UTI	43,871	$124,073	$56,707	$58,293	$14,971	$5,443,252,297	$2,493,666,413	$2,949,585,884
Asthma	320,261	$76,795	$63,140	$67,415	$14,203	$24,594,458,656	$20,224,825,240	$4,369,633,415
							Total Increase	$66,891,065,940

Calculation of statewide incremental HAI cost

From the THCIC inpatient discharge, I identified the number of PPH with HAI by type of HAI (Table 21). Using the incremental hospitalization cost associated with each HAI and the six month follow-up cost estimated to be attributable to each type of HAI, the total incremental cost of HAI in Texas during 2011 was estimated to be over $31 million. CDI contributed the most cost due to the higher prevalence in the THCIC discharge data. While the incremental cost of VAP was nearly double the incremental cost of CDI during hospitalization, the follow-up cost for CDI was nearly 5 times that of VAP. The estimated total incremental cost of HAI would likely be much greater if the limitations for identifying SSI and CAUTI from discharge data could be overcome.

Table 21. Incremental cost of HAI by HAI in Texas

	PPH with HAI	Incremental HAI hospitalization cost[1]	Incremental HAI follow-up cost[2]	Total Incremental HAI cost
CDI	530	$17,040	$11,467	$15,108,846
CLABSI	133	$32,408	-$1,716	$4,082,157
CAUTI	109	$13,118	$17,578	$3,345,909
VAP	258	$32,541	$1,977	$8,905,714
				$31,442,627

1. All estimates are adjusted for demographic, health status, community and hospital characteristics
2. All estimates are adjusted for demographic characteristics and health status

To identify the incremental cost of HAI associated with the uninsured, I used the distribution of the PPH with HAI population by payer identified in the descriptive analyses (Table 22). The bulk of incremental HAI costs are paid by Medicare, private insurers and Medicaid at $20.7 million, $4.7 million, and $3.4 million, respectively

(Table 22). The uninsured accounted for 7% of incremental HAI costs at $2.1 million (Table 22).

Table 22. Incremental cost of HAI by payer

Primary Payer	% of PPH with HAI Population	Total Incremental HAI Costs
Private payer	15%	$4,727,068
Medicare	66%	$20,707,608
Medicaid	11%	$3,385,191
Other Gov't	2%	$518,453
Self-pay or Charity	7%	$2,104,308

Sensitivity to changes of insurance rates

It is unrealistic to assume 100% participation of the uninsured in newly available insurance options and that 100% of PPH are preventable through access to preventive care. Additionally, uncertainty and variation in estimates of participation in the new insurance marketplaces exists. Another factor influencing hospitalization is the quality of care available. To account for these uncertainties, I created a table that tracks changes in rates of the uninsured and the percent of the PPH with HAI that is uninsured. The incremental analysis reflects sensitivity to take-up rates of new insurance options and the whether the care the uninsured receives for ACSC is sufficient to avoid a PPH.

From the sensitivity analysis, we observed the greatest effect on the difference in preventive care and incremental HAI costs from the transition of individuals from uninsured to insured, accounting for decreases of approximately $14 billion for a 5%

decrease in the uninsured rate (Table 23). Since transition from uninsured to insured does not assure receipt of quality preventive healthcare, I changed the percentage of uninsured for the PPH with HAI population to reflect reductions in PPH due to receipt of quality healthcare. For each percent decrease of the uninsured in the PPH with HAI population, we observed an estimated decrease in incremental costs of $0.3 million (Table 23).

Table 23. Sensitivity of incremental costs to state uninsurance rate and percent of uninsured PPH with HAI

% of PPH with HAI population in Texas hospitals that is uninsured	% of Texas population that is Uninsured	24%	20%	15%	10%	5%	3%	1%
		In Millions of dollars						
7%	Preventive care	66,891.1	55,668.6	41,738.5	27,808.5	13,878.4	8,306.4	2,734.4
	Incremental HAI	2.1	2.1	2.1	2.1	2.1	2.1	2.1
	Preventive-HAI	66,889.0	55,666.5	41,736.4	27,806.4	13,876.3	8,304.3	2,732.3
6%	Preventive care	66,891.1	55,668.6	41,738.5	27,808.5	13,878.4	8,306.4	2,734.4
	Incremental HAI	1.9	1.9	1.9	1.9	1.9	1.9	1.9
	Preventive-HAI	66,889.2	55,666.7	41,736.6	27,806.6	13,876.5	8,304.5	2,732.5
5%	Preventive care	66,891.1	55,668.6	41,738.5	27,808.5	13,878.4	8,306.4	2,734.4
	Incremental HAI	1.6	1.6	1.6	1.6	1.6	1.6	1.6
	Preventive-HAI	66,889.5	55,667.0	41,737.0	27,806.9	13,876.8	8,304.8	2,732.8
4%	Preventive care	66,891.1	55,668.6	41,738.5	27,808.5	13,878.4	8,306.4	2,734.4
	Incremental HAI	1.3	1.3	1.3	1.3	1.3	1.3	1.3
	Preventive-HAI	66,889.8	55,667.3	41,737.3	27,807.2	13,877.2	8,305.1	2,733.1
3%	Preventive care	66,891.1	55,668.6	41,738.5	27,808.5	13,878.4	8,306.4	2,734.4
	Incremental HAI	0.9	0.9	0.9	0.9	0.9	0.9	0.9
	Preventive-HAI	66,890.1	55,667.7	41,737.6	27,807.5	13,877.5	8,305.4	2,733.4
2%	Preventive care	66,891.1	55,668.6	41,738.5	27,808.5	13,878.4	8,306.4	2,734.4
	Incremental HAI	0.6	0.6	0.6	0.6	0.6	0.6	0.6
	Preventive-HAI	66,890.4	55,668.0	41,737.9	27,807.8	13,877.8	8,305.8	2,733.7
1%	Preventive care	66,891.1	55,668.6	41,738.5	27,808.5	13,878.4	8,306.4	2,734.4
	Incremental HAI	0.3	0.3	0.3	0.3	0.3	0.3	0.3
	Preventive-HAI	66,890.8	55,668.3	41,738.2	27,808.2	13,878.1	8,306.1	2,734.1

Limitations

THCIC data

Limitations in the THCIC inpatient PUDF centered on the inability to identify SSI and CAUTI. For SSI, the inability to link a patient across time prohibited identification of SSI beyond the initial surgical procedure. As CAUTI has been identified by the CDC as the most common HAI, limitations of administrative coding practices for CAUTI resulted in limited ability evaluate the total effects of CAUTI on cost and utilization in this study. Finally, limitations extended to accounting for effects related to the comorbid conditions for AIDS, alcohol abuse, and drug abuse. The limitations center on suppressed diagnosis codes and age for patients with these conditions in the THCIC inpatient PUDF.

BCBSTX data

While appropriately populated variables included age, gender, principal diagnosis and date of service, other evaluation variables such as race, present on admission, and facility specific data did not exist in the data. Unavailable present on admission information limited my ability to assuredly identify HAI over community acquired CDI, and missing procedure date limited my ability to identify duration of ventilation when evaluating VAP. Additionally, since no geographic identifier existed in the data, and facility specific identifiers could not be linked to hospital survey information, community factors such as rurality, availability of public benefits, or other facility specific information could not be included in regression analysis. The inability to

assign variation in cost and utilization by these variables should be considered when comparing costs and utilization between the THCIC and BCBSTX data.

CHAPTER VI

DISCUSSION

The PPH, HAI, PPH with HAI, and general inpatient populations

Individuals with a PPH are more likely to be older, white, females when compared to the general inpatient population. Although the 45-64 years of age population appears to be the largest single age group, when I combined the 65 and over categories, we observe that 65 and over accounts for nearly half of the PPH population. This is consistent with the fact that approximately 54% of PPH patients specified Medicare as their primary payer. The proportion of the uninsured was slightly greater in the PPH population than the general inpatient population, accounting for 10% of the PPH population and only 9% of the general inpatient population. The increased proportion in the Medicare payer group was offset by decreases in the proportion of individuals specifying private insurance or Medicaid as their primary payer.

For the HAI population, we observed a similar demographic composition as the PPH population. However, for the HAI population, 56% of patients were 65 and over. The increased proportion of 65 and over in the HAI population was reflected in the proportion of individuals that specified Medicare as their primary payer (62%). As the proportion of Medicare beneficiaries grows, we observed major decreases in the proportion of private (11%-17% decreases) and Medicaid (8%-12% decreases) payer groups while the uninsured decreased in proportion for HAI (6%), but maintained the proportion of admissions for PPH with HAI (7%).

When we consider these changes in population composition in isolation, the changes suggest three things. First, that the Medicare population is at greater risk than other groups for a PPH, HAI, and a PPH with HAI. Second, that private payers and Medicaid beneficiaries are at less risk for PPH, HAI, and PPH with HAI, Third, the uninsured's risk is minimal for PPH and slightly decreased for HAI and PPH with HAI. However, when we consider that Medicare beneficiaries are mostly 65 and over, that Medicaid primarily covers children, that private insurance primarily covers members of a family with a healthy working individual, and the uninsured avoid utilization unless absolutely necessary, the proportional changes in demographic composition of the populations are not surprising. The demographic descriptive analysis does illuminate the need for additional research regarding the effects of PPH and HAI on the Medicare population, since they are the majority population of those affected with PPH, HAI, and PPH with HAI.

The ability to identify HAI from administrative data

Identified issues

The ability to identify HAI from administrative data using cross-sectional methods allows researchers to analyze and identify associations between HAI and other factors such as PPH. However, the cross-sectional methods were limited by specificity in ICD-9-CM codes and administrative coding practices. For example, where multiple ICD-9-CM codes are required to capture a single event, there is no method for researchers to link the information together without review of the clinical record. Aside from the principal diagnosis, ICD-9-CM codes are usually listed according to level of

compensation rather than clinical importance or date of occurrence. While procedures include date of procedure in the THCIC inpatient PUDF, it is impossible to tell whether an infection diagnosis is a result of a procedure, the reason for the procedure or unrelated. The inclusion of present on admission information for each diagnosis has improved researchers' abilities to make chronologically valid assumptions, but it is not infallible.

One example is the under identification of CAUTI, the most common HAI. There are numerous UTI diagnosis codes including a code for CAUTI (ICD-9-CM code 996.64). Other researchers have also found CAUTI under identified with the ICD-9-CM code 996.64. An option for researchers is to use the other UTI diagnosis codes, present on admission information, and evidence of urinary catheterization to identify infection that started after admission. However, it is difficult for researchers to reliably link the UTI diagnosis with urinary catheterization. For some reason, information about CAUTI is either not captured in the clinical record or it is not translated in a consistent way to the administrative discharge abstract.

For VAP, cross-sectional methods were more successful in identifying cases of VAP, but the method faces similar challenges as CAUTI. Similarities are related to the ability to identify pneumonia, ventilation, and present on admission information for pneumonia, but our ability to reliably link the three things together for a VAP diagnosis could create both under, over, and misidentification.

For identifying SSI, ICD-9-CM codes specify surgical procedures and infections associated with bodily location. When surgery codes and infection codes are combined

with present on admission information, we can identify SSI during the initial hospitalization. However, SSI may take up to 90 days after surgery to manifest sufficiently for diagnosis by a physician. Therefore, infection identification may not occur during the same hospitalization as the surgery. Additionally, treatment of SSI may or may not involve additional hospitalization. Where additional hospitalization occurs, and if hospitalizations for an individual were linked across time and facilities, SSI might be more reliably identified through the inpatient discharge abstract. Given the course of disease and the identification process, claims data may be a more reliable source for identifying SSI and SSI costs. However, the use of claims data limits identification to single payers limiting our ability to compare multiple groups especially the uninsured.

For CDI, cross-sectional methods of identification appeared to identify CDI sufficiently. The primary issue with CDI identification is related to differentiating between community and hospital acquired CDI. The present on admission information can rule out some of the community acquired CDI individuals. Length of stay can also be used to eliminate community acquired, but only for individuals with inpatient stays less than three days, as CDI requires 2 to 3 days to manifest symptoms.

Another important explanatory factor for CDI is antibiotic use during hospitalization. Since the THCIC inpatient PUDF does not contain pharmaceutical information, this limits the ability to chronologically determine when antibiotics where given relative to symptomatic CDI being diagnosed. The reason this relationship is important is that it may differentiate some individuals as community acquired rather that hospital acquired.

Another consideration for CDI includes previous hospitalization within 3 to 6 months. As CDI is a long living spore, a post-discharge need for antibiotics may result in CDI being identified as community acquired rather than as the subsequent episode of healthcare associated CDI. As strategies to reduce other HAIs have met with measurable success, CDI has proven difficult to restrain. While healthcare quality strategies have mostly contained CDI, our inability to reduce occurrence requires continued research to understand the transmission of CDI.

Finally, consistent with recently published rates of CLABSI, we see in 2011 lower than expected rates of CLABSI suggesting a ramp up effect of quality or patient safety initiatives targeted at reducing the occurrence of CLABSI in response to implementation of non-payment strategies by CMS. Since the methodologies for identifying CLABSI are validated by AHRQ, CMS, and NQF, the lower than expected identification of CLABSI is likely due to hospitals' response to non-payment of HAI. Another contributing factor is possible changes in administrative coding practices. Since CMS annually publishes conditions for non-payment and the ICD-9-CM codes associated with those conditions, hospitals may also respond by changing coding strategies that contribute to the reduced identification of CLABSI. However, given the focus on reduction of HAI, the effects we observe in the data are consistent with other surveillance initiatives (U.S. Department of Health and Human Services, 2014).

Potential solutions

Since the bulk of issues for identifying HAI from administrative data are related to coding practices, I have generated a potential solution that should not create

substantial additional reporting burden, and would greatly enhance our ability to assign diagnosis codes to relevant groups of healthcare provision. Append diagnoses codes with one letter for each group of codes that describe a single event. For example, all diagnosis fields would start with a letter. Principal diagnosis would start with the letter "A". In secondary diagnosis fields, if the diagnosis code started with "A", it would further describe the primary reason for hospitalization. Each subsequent diagnosis would start with a different letter for each "grouping" of diagnosis codes. This allows diagnosis for pathogens to be linked to the diagnosis for infection site. For the state of Texas, only 25 diagnosis codes are recorded, so if all 25 diagnosis fields were independent and used, a letter could be used for each field without duplication. In consideration for other states that report up to 30 diagnosis codes per admission, an alternative would be no letter at the beginning of a diagnosis code or a blank for stand-alone diagnosis. Either strategy would provide researchers and potentially payers with easily disseminated information about a healthcare event. This method could also be extended to include procedure codes.

The potential down side to this strategy is the time and resources for additional training required for providers and coders. For example, providers may be required to include more information when charting patient information to allow administrative coders to appropriately apply the new scheme. Other resource concerns may involve the additional time coders' need to assure they capture the relevant information in the clinical record. Another consideration is the transition from ICD-9-CM to ICD-10 codes.

Since ICD-10 codes include substantially increased specificity, additional research with ICD-10 codes would illuminate whether this strategy is relevant or practical.

Odds of PPH with HAI

Because PPH with HAI is a rare event, 37 in every 100,000 admissions, and the large sample size was likely to detect the smallest changes as significant, I decided that large effects that were statistically significant would provide the most information about PPH with HAI. For the odds ratio analysis, I defined a large effect to be an odds ratio less than .5 or greater than two. While many effects were large or near large, only a few were significant.

Perhaps counter-intuitive, for most individuals with a PPH, the odds of acquiring an HAI was less than the odds of the general inpatient population acquiring an HAI during hospitalization. What I anticipated as reduced health status that placed PPH patients at greater risk for an HAI, turned out to be less acute disease when compared to other inpatients. The possible explanations for lower odds of HAI included non-PPH individuals with health issues more frequently requiring central lines, urinary catheters, mechanical ventilation, or surgery than PPH patients.

Overall, individuals with a PPH had odds of acquiring CDI that was approximately half of the non-PPH population, and the odds of acquiring VAP was a third of the odds when compared to the non-PPH population. Other significant effects reported odds ratios of 0.6 or less except for diabetes related lower extremity amputation. Diabetes related lower extremity amputation was the only PPH that demonstrated an odds ratio greater than 1 for all four types of HAI evaluated. The largest

effect between CDI and diabetes related lower extremity amputation was significant and measured PPH patients' odds of acquiring CDI as 2.9 times that of non-PPH patients. Also significant for diabetes related lower extremity amputation was VAP where the odds of PPH patients acquiring VAP were 1.44 times the non-PPH population.

At the other extreme of large effects, we observed patients admitted for bacterial pneumonia or urinary tract infection had odds ratios below 0.1 for VAP. This translates to the general inpatient population odds of acquiring VAP at more than ten times the PPH patients. These significantly lower odds of acquiring HAIs beg us to ask how else the PPH patients might be different.

When we examined the odds of acquiring HAI by payer, we observed Medicare beneficiaries odds for acquiring CDI was nearly twice that of other payer groups. For other types of HAI, effects were not as large and varied in regards to significance. With the payer variable significant in the logistic regression models for predicting HAI, two possible and likely explanations exist for differences between payer types. First are the age and health status of the beneficiaries represented by each payer. A second consideration is government verses non-government payers. Since the different payer types represent the elderly (Medicare), the working healthy (Private Insurance), children (Medicaid), special needs or military (Other government), and the poor (Charity or self-pay), it is plausible that each group in addition to variation captured by age, will have unique and specific needs and utilization. Regarding government verses non-government, it is plausible that due to the government being held to different standards of accountability, transparency, and performance, differences in care delivery as dictated

by payer are absorbed by the payer variable. Either way, additional research to tease out these differences would be beneficial.

Costs

Analysis of costs

The cost models accounted for variation in cost by adjusting for approximately 790 other variables. These variables accounted for significant variation associated with gender, age, race, hospital ownership, type of room, comorbid conditions and primary diagnosis as represented by DRG. While not all categories were significant, DRG absorbed the most variation, since DRG is a reflection of mean cost of consumed services for a given diagnosis. In determining whether to include DRG, the primary analytic concern was sample size and over specification. To assure sufficient sample size was available, a variable inflation factor was used when estimating required sample sizes (Hsieh, Bloch, & Larsen, 1998). Since PPH with HAI is a rare event that has not been previously studied, a large effect was determined to be the best choice and guided sample size calculations. Additionally, since there were very few pediatric PPH with HAI, all cost analysis were limited to the adult population. With these considerations, sample size calculations revealed that there was a sufficient number of observations to use DRGs and still detect large effects related to PPH and HAI.

Cost associated with hospitalizations

In addition to the reduced odds of acquiring HAI in the PPH population, the mean hospitalization cost was less for PPH patients when adjusted for demographic, health status, hospital, and community characteristics. On average, PPH hospitalizations

were approximately $2,100 less than the mean cost of other hospitalizations. Consistent across the different types of HAI, the PPH for heart failure cost slightly more than other hospitalizations between $400 and $500, while the remaining PPH mean costs were from $1,100 to $4,000 less than the general inpatient population. Again, the effects were significant at a $p<.05$ level.

Like the odds ratio analysis, we may have anticipated costs per hospitalization to be greater due to the reduced health status of PPH individuals. However, what we observed was ACSC related hospitalization required fewer resources to stabilize, with the exception of individuals with heart failure, leading to lower on average cost per hospitalization when compared to the non-PPH population. While this may seem counter intuitive, when we reflect on the need for surgery and other high intensity services to stabilize a PPH patient, with the exception of diabetes related lower extremity amputation, it seems plausible that mean PPH cost less than the general inpatient population.

When we examined mean costs by payer, we observed that patients with private insurance consistently had a higher mean cost by more than $2,000 when compared to Medicare and Medicaid, and nearly $4,000 more when compared to the uninsured. These cost differences are adjusted for demographics, health status, hospital and community characteristics as well as DRG diagnosis. This causes us to question whether there are differences in services provided to privately insured patients, or whether private insurers are paying more for similar services. While we know providers are required to assess

and stabilize the uninsured, the question remains why there are such large differences in cost for the privately insured, the governmentally insured, and the uninsured.

Preventive and follow-up care costs for the PPH population

For individuals with a PPH, we observed costs of preventive care before hospitalization that were noticeably less than the annual cost of preventive care for the corresponding ACSC condition with the exception of lower extremity amputation. Preventive care costs for the PPH population were approximately half of the corresponding ACSC population with the exception of diabetes related lower extremity amputation where mean annual preventive care was more than two and half times diabetes ACSC annual preventive care costs. After hospitalization, we observed that the six-month follow-up cost of preventive care was nearly equivalent to a full year of preventive care by the same individuals in the year prior to the PPH admission.

The differences in preventive care costs before and after a PPH suggest changes in utilization patterns for the PPH population. It appears insured individuals who underutilize preventive care in managing an ACSC, increase utilization to near "normal" levels after a hospitalization.

For the purposes of answering the research question, I assumed that the uninsured used healthcare prior to a PPH in a similar way as the BCBSTX PPH population. I used these preventive care costs as a proxy for the uninsured, because although previous research estimates that the uninsured use preventive care less than insured individuals, it also shows the uninsured access care through more expensive channels such as the emergency room (Bradley, Gandhi, Neumark, Garland, & Retchin,

2012). While utilization may be similar, given the significant differences in hospitalization cost by payer type, I also assume that using the BCBSTX preventive care costs overestimates the cost of utilization. By using the BCBSTX preventive care estimates, we account for the maximum cost to transition the uninsured to insured.

Costs associated with HAI

As expected, the mean effect of HAI on hospitalization costs was significant and substantial. Additional mean cost during hospitalization was approximately $13,100, $17,000, $32,400, and $32,500 for CAUTI, CDI, CLABSI, and VAP respectively. Even with the mean decrease in hospitalization costs associated with a PPH, the mean increase in hospitalization costs associated with HAI clearly added substantial financial burden to patients who acquired an HAI during hospitalization.

Unfortunately, for individuals who acquire an HAI during hospitalization, there are additional costs associated with post-hospitalization care. Although CLABSI incremental hospitalization costs were the second highest, the incremental cost in follow-up care was approximately $1,700 less than other PPH patients with no CLABSI. For VAP, the most expensive HAI, follow-up costs added to the financial burden with nearly $2,000 more of follow-up care for individuals with VAP during a PPH. For CDI and CAUTI, incremental cost of follow-up care were approximately $11,500 and $17,600 respectively. This makes the total incremental cost of HAI range from $28 thousand to nearly $35 thousand per person. This translates to over $31 million of healthcare expenditures attributable to HAI in the adult PPH population.

To answer the research question, I needed an estimate of incremental cost of HAI for the uninsured with a PPH. By multiplying the total incremental cost of HAI in the PPH population by the proportion of uninsured in the PPH with HAI population (7%), I estimated that the uninsured accounted for $2.1 million in healthcare expenditures attributable to HAI in the PPH population. This estimate is likely an underestimation due to the under identification of CAUTI and SSI. Since the $2.1 million is attributable to 69 individuals, and SSI has been identified as the most expensive HAI, identification of SSI in the uninsured population may substantially change the estimate. While the cost of care for CAUTI was similar to the other HAI, if we raised the number of individuals in the PPH with CAUTI to match the CDI levels, the costs attributed to HAI in the uninsured PPH population increased by nearly thirteen million dollars.

Costs associated with preventive care for ACSC

The other cost estimate required to answer the research question was the increase in healthcare cost to provide preventive health care to the uninsured ACSC population in Texas. Using the proportion of individuals with each ACSC as estimated by the Texas DSHS or by the CDC and estimates of preventive and follow-up care cost from the BCBSTX population, I estimated costs for existing utilization by the uninsured, and estimated utilization if all uninsured ACSC individuals became insured. To provide a genesis for testing changes in uninsurance rates and the proportion of the uninsured in the PPH with HAI population, I made three additional assumptions to facilitate a maximum estimation. First, I assumed that the entire uninsured ACSC population would participate fully in preventive healthcare once insured. Second, I assumed that all PPH

were preventable. Third, I assumed the proportion of the inpatient population with PPH and HAI would not change. While the first two assumptions are not reasonable to expect, they provide a starting point for sensitivity analyses regarding uninsurance rates, and the effect access to preventive care is hypothesized to have on PPH.

With the exception of asthma and congestive heart failure, preventive healthcare costs per person in the ACSC population were nearly double the total annual expenditures by the PPH population. For the uninsured with asthma, annual healthcare expenditures would increase by approximately 20%, and for the uninsured with heart failure, annual expenditures would increase three fold. When aggregated across all ACSC, the increase in healthcare spending was estimated at $66.8 billion.

With analysis limited to the PPH conditions that also experienced measurable HAI, the estimate likely understates the increase in healthcare expenditures for moving the uninsured to being insured. Other phenomena likely to play a role in the consumption of healthcare services for the uninsured include pent-up demand creating spikes in utilization, continued misuse of preventive services, and limitations in participation due to immigration status. The effects of pent-up demand may lead to increases in PPH such as those seen when Oregon expanded Medicaid (Saha, Solotaroff, Oster, & Bindman, 2007). Continued misuse of services may be curbed through spill-over effects as Medicare and Medicaid penetrate markets with their managed care products (Baicker, Chernew, & Robbins, 2013). Finally, immigrants not eligible to participate in the health insurance marketplace, may continue to under use healthcare as immigrants account for up to 22% of the uninsured in Texas (Hoffman, Schwartz, Tolbert, Cook, & Williams,

2007; Lorden, 2008). These effects should be considered when discussing policy to increase access to preventive care and reduce PPH.

The role of insurance

In addition to the increased cost associated with private insurance, we observed no cases of HAI in the diabetes related lower extremity amputation PPH for the BCBSTX population. This is interesting as the general inpatient population of diabetes related lower extremity amputation patients were the most likely to acquire an HAI. This may be attributable to the overall younger BCBSTX population, or the substantial preventive care received by the diabetes related lower extremity amputation BCBSTX beneficiaries both before and after hospitalization. This finding also highlights the fact that not all PPH are preventable. Additionally interesting, none of the BCBSTX diabetes related lower extremity amputation patients acquired an HAI despite being in the most likely group. This brings into question whether privately insured individuals are treated differently during hospitalization or whether privately insured individuals systematically seek out providers and facilities with higher quality practices.

Since Medicare beneficiaries are disproportionately admitted for PPH and disproportionately acquire HAI during hospitalization, additional research is needed to discover whether Medicare beneficiaries are different simply due to age or if other definable attributes exist. Other potential reasons that may explain increased risk of PPH or HAI may include community verses institutional living, presence of an active patient advocate, ACSC as a comorbid condition to diseases that create an immunocompromised state, or beneficiary within a year of death. With the Medicare

population accounting for over $20 million in healthcare expenditures related to PPH with HAI in Texas, any insight may reduce spending and improve the quality of remaining life for elders.

Sensitivity to uptake and use of preventive care

Once costs for preventive healthcare and incremental cost of HAI were calculated, I changed rates of uninsurance and the percentage of uninsured in the PPH with HAI population to estimate the effect of newly available insurance options. A 1% decrease in the uninsurance rate translated to approximately a $2.8 billion decrease in the estimated total cost to insure the uninsured ACSC population. To date, just over 12% of the uninsured in Texas have enrolled into health insurance plans through the federal insurance exchange. The enrollment should translate into a decrease in the estimated total cost to insure the uninsured ACSC population by approximately $8 billion. If there is initial adverse selection, a higher proportion of the newly enrolled uninsured individuals will have an ACSC than compared to the state prevalence levels. While enrollment will translate to reductions in the cost estimate, it may also provide researchers with the ability to track the effects of pent-up demand for the newly insured.

Limitations

There were three limitations within this study. First, administrative inpatient discharge data was limited through issues of coding specificity and the ability to link infections with procedures with certainty leading to under identification of CAUTI and potentially VAP. Identification of SSI was limited due to inability to link infection to

past surgical admissions or with non-hospital utilization. The under or potentially mis-identification of HAI translates to unidentified costs and effects of HAI.

Second, preventive care cost estimations are based upon private insurance claims data. Since private insurance is associated with more expensive utilization, the BCBSTX preventive care costs may over estimate the cost of preventive care services used by the uninsured and individuals with other payers. As the uninsured move to insured status, they are likely to choose health insurance plans similar to Medicaid or Medicare in cost, because they are accessing insurance through the health insurance exchange or Medicaid.

Finally, pre and post PPH utilization for the BCBSTX PPH population are likely to overestimate current utilization by the uninsured. Since most uninsured are assumed to have financial barriers to insurance, individuals with insurance will not have the same financial barriers when accessing healthcare as the uninsured. The differences between utilization misuse of preventive services and under-use due to insurance barriers may be very different from one another.

While study results are generalizable, these three limitations suggest that context is necessary when interpreting the results.

Policy implications and future research

To provide preventive care for individuals with ACSC equates to an average increase of between $11,000 and $15,000 per uninsured individual in Texas. If the decision to expand insurance options were based solely on cost savings related to PPH with HAI, there is no compelling evidence. However, at $2.1 million of potentially

avoidable cost, the cost of HAI in the PPH population should be part of the preventive care and HAI discussions.

Another consideration for the policy discussion regarding expansion of insurance for preventive care is the existence of other unidentified or under quantified rare events within the ACSC population. For PPH with HAI, 69 individuals accounted for $2.1 million of potentially avoidable healthcare costs. If other similar groups exist within the uninsured ACSC population, and preventive care provides a direct or theoretical solution to the issue, the financial argument for not expanding insurance options becomes less compelling.

Is it really about access in preventive care?

With the majority of PPH admissions designated as insured individuals, I speculate that three things are occurring simultaneously. First, individuals with a PPH are not accessing preventive care in a timely manner. Second, since the PPH population is primarily composed of Medicare beneficiaries, I suspect lack of a patient advocate or institutional living may play a significant role in timely access to care. Finally, for the entire PPH population, the question remains as to the quality of preventive care received. Claims analyses focused on providers with PPH patients may illuminate care settings, living situations or quality metrics associated with PPH.

Is it about age?

Since the majority of individuals in the PPH, HAI and PPH with HAI are Medicare beneficiaries, and the majority of Medicare beneficiaries qualify for Medicare due to age, is it about age or nearness to death rather than access. Exploring the

Medicare PPH population utilization characteristics and mortality may explain the disproportionate share of Medicare beneficiaries in the PPH population.

Is it about quality of preventive care?

Since over 90% of individuals with a PPH have insurance, we must ask if it is the quality of care. As suggested for the Medicare population, claims analyses focused on providers with PPH patients may illuminate care settings, living situations or quality metrics associated with PPH.

Is it about patterns in utilization?

Since we observed different preventive care cost patterns between the BCBSTX PPH and ACSC populations, I speculate that individuals with a PPH and insurance either do not access preventive care in a timely manner or they are non-compliant with provider recommendations for self-care. Claims analysis examining first diagnosis of an ACSC in relation to a PPH would illuminate whether individuals are non-compliant or are unaware that they have an ACSC. Another approach would be a longitudinal look at preventive care by six-month intervals for one year prior to PPH and two years post PPH.

CHAPTER VII

CONCLUSIONS

For Texas, the estimated increase in healthcare spending to provide preventive healthcare through insurance for uninsured adults with an ACSC was $66.8 billion. When spread across the uninsured population, the cost equates to an $11 thousand per person increase in healthcare spending. For the PPH population, if preventive care translated to avoiding hospitalization, the spending for preventive care would less than the hospitalization costs that range from $12 to $15 thousand for a PPH. For individuals who acquire an HAI during a PPH hospitalization, an addition $15 thousand of hospitalization cost and $15 thousand of follow-up care could also be avoided. However, only a small portion of the Texas uninsured admitted for a PPH acquired an HAI, therefore the incremental HAI costs of approximately $2.1 million does not produce sufficient justification for the expansion of insurance options.

Regardless of this conclusion, this study has illuminated two important issues. First, $31 million in additional healthcare expenditures were attributed to the effects of HAI on approximately one thousand patients with PPH in Texas during 2011. The additional healthcare expenditures merit investigation into methods to reduce the ultimate source, HAI. This is especially true, since the estimated $31 million is likely an underestimation of HAI in the PPH population due to the limitations in administrative discharge data to identify HAI, especially CAUTI and SSI. Second, 90%, 94%, and 93% of the PPH, HAI, and PPH with HAI populations were insured. Given that insurance related access to preventive healthcare services should theoretically translate to lower

rates of PPH, we must ask what other changeable factors besides insurance related access would reduce PPH.

HAI in the Texas PPH population

An HAI is an unfortunate outcome when individuals have an encounter with the healthcare system. Since identifiable CDI, CLABSI, VAP, and CAUTI accounted for an estimated $31 million of additional healthcare expenditures for 1,031 of the nearly 15,000 individuals with an HAI during hospitalization, any method to reduce HAI occurrence is worth considering. The outcome of this study supports HAI focused initiatives as more productive in reducing HAI than initiatives that reduce exposure to risk such as initiatives that reduce PPH. Although most PPH patients were less likely to acquire an HAI compared to the general inpatient population, individuals admitted with diabetes related lower extremity amputation experienced odds of acquiring CDI 2.9 times that of the general inpatient population, and their odds of acquiring any HAI was 1.4 times that of the general inpatient population. Because of the increased odds of acquiring an HAI, it may be beneficial for the diabetes related lower extremity amputation population to be the focus of both additional preventive healthcare strategies and in-hospital strategies to reduce acquisition of HAI. Another group identified in this study at potentially higher risk of an HAI during a PPH were Medicare beneficiaries as their odds of acquiring an HAI were twice that of any other payer group. Research that answers why Medicare beneficiaries are disproportionately hospitalized for ACSC, and why Medicare beneficiaries acquire HAI more frequently than any other payer group

may prove beneficial in generating strategies for reducing PPH, HAI, and PPH with HAI.

Since CAUTI and SSI were under identified in this study, the conclusions I make here are speculative. However, since most PPH do not require surgical intervention, SSI is likely to maintain low levels in the PPH population. Despite that fact, we still must take the few cases that occur into account as other studies identified SSI as the most expensive form of HAI (Vinyard, 2013; Zimlichman et al., 2013). As such, better methods of identification may pinpoint whether PPH play any role in identifying an at risk population.

More concerning is the effect CAUTI may have on the PPH population. The CDC identified CAUTI as the most frequently occurring HAI (Center for Disease Control and Prevention, National Center for Emerging and Zoonotic Infectious Diseases, & Division of Healthcare Quality Promotion, 2012a; Saint et al., 2006). Yet, only SSI was identified less often for the inpatient population using the methods specified. With a mean incremental hospitalization cost of $13 thousand, and an estimated mean incremental follow-up cost of $17 thousand, the additional $30 thousand per person could translate to tens of millions of dollars in under identified cost for CAUTI. Better identification of CAUTI would allow for more accurate cost estimates and provide insight into which are the most vulnerable populations regarding CAUTI.

Finally, given the financial and physical costs associated with HAI, reduction of HAIs has been the focus of multiple quality initiatives combining the expertise of a variety of stakeholders. In a preliminary report examining the effect of such initiatives

on HAI rates between 2010 and 2012, substantial reductions occurred for CLABSI, CAUTI, SSI, and VAP in participating Hospital Engagement Networks (U.S. Department of Health and Human Services, 2014). With some reductions as high as 43%, the translation to improved health outcomes and cost savings will be substantial.

Cause and effect of insurance on PPH

While insurance plays a vital role in reducing barriers in access to healthcare, especially preventive healthcare services, the majority of individuals with a PPH in 2011 in Texas had insurance at the time of hospitalization. This is not surprising when viewed in the light of previous research where the Medicaid expansion in Oregon preceded increases in the number of PPH in the newly insured (Baicker et al., 2013; Saha, Solotaroff, Oster, & Bindman, 2007). While the increase in PPH in Oregon was attributed to pent-up demand in the Medicaid population, 75% of the PPH in Texas during 2011 was attributed to patients with Medicare or private insurance suggesting that most were not newly insured.

Additionally, if preventive care is the key to reducing PPHs, and the majority of the PPH population in Texas is insured, other barriers may exist to preventive care. Possible barriers include gaps in patient knowledge about how to manage ACSC through preventive healthcare or how to effectively interact with the healthcare system. Another potentially important barrier may be that access through insurance does not translate to access of quality preventive care. The analysis of cost in the PPH BCBSTX population suggests the PPH population utilizes preventive care services differently than ACSC counterparts without a PPH. While annual utilization costs by PPH individuals is

approximately half when compared to the annual ACSC without PPH population costs, we observed increased utilization costs by the PPH population after hospitalization up to a similar level as the ACSC population. It is likely due to follow-up care associated with the PPH, however, it is also possible the PPH may work as an expensive educational experience for insured individuals in how to manage an ACSC through preventive care services.

Future research

From the results of this study, I have identified three areas where additional research would fill gaps in our knowledge.

PPH and the Medicare population

With such a large proportion of the PPH, HAI, and PPH with HAI population listing Medicare as their primary insurer, identifying individuals at risk of a PPH in a timely manner could substantially reduce expenditures by Medicare, while simultaneously improving quality of life of Medicare beneficiaries, and others through spillover effects. While continuity of care, comorbid conditions, and dual-eligibility are previously identified associations, other areas of research may include community dwelling verses institutional living, presence and type of care advocate, or age of onset and ACSC self-care and management education.

Changes in utilization surrounding a PPH event

The change in utilization cost before and after a PPH demonstrated by the BCBSTX PPH individuals provides us with an opportunity to understand how insured individuals with a PPH use healthcare. Since insurance status has been linked to better

health and improved outcomes, understanding utilization of services by individuals with an ACSC that underutilize healthcare despite access through insurance may illuminate our theoretical understanding of healthcare utilization. Additionally, the BCBSTX PPH population had increased utilization costs after the PPH event suggesting either follow-up care was necessary or there was a change in utilization patterns. Since costs increased after the PPH, a longitudinal approach to analyze healthcare utilization by insured PPH individuals should answer whether changes were permanent. We should also consider or validate whether geographic availability of services was cause of underutilization prior to the PPH.

Identification methods for CAUTI and SSI

Finally, although other methods are used for surveillance of HAI, the ability to identify HAI in administrative data allows researchers to identify relationships and costs through secondary analysis of large datasets. Administrative discharge data or claims data are currently the most consistent and readily available sources of information to researchers. While coding and coding practice changes would enable researchers to better identify CAUTI or SSI from administrative data, other sources of information may be on the horizon, such electronic healthcare records (EHR). As healthcare informatics evolves, the availability of EHR information may prove to be better equipped in providing researchers with the necessary information to identify CAUTI and SSI. Since EHR data is unlikely to contain cost or payment information, EHR data sources may allow us to accurately identify HAI, but may limit our ability to cost HAI.

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APPENDIX

DIAGNOSIS AND PROCEDURE CODES FOR PPH AND HAI IDENTIFICATION

Condition to identify	ICD-9-CM code or HCPCs code	Source
Diabetes	24900	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24901	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24910	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24911	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24920	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24921	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24930	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24931	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24940	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24941	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24950	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24951	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24960	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24961	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24970	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24971	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24980	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24981	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24990	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	24991	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25000	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities

Condition to identify	ICD-9-CM code or HCPCs code	Source
Diabetes	25001	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25002	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25003	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25010	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25011	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25012	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25013	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25020	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25021	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25022	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25023	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25030	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25031	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25032	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25033	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25040	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25041	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25042	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25043	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25050	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25051	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25052	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25053	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25060	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25061	CMS Chronic Condition Warehouse and

Condition to identify	ICD-9-CM code or HCPCs code	Source
		Elixhauser/HCUP comorbidities
Diabetes	25062	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25063	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25070	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25071	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25072	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25073	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25080	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25081	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25082	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25083	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25090	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25091	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25092	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Diabetes	25093	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
COPD	490	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
COPD	491	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
COPD	4910	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
COPD	4911	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
COPD	49120	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
COPD	49121	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
COPD	49122	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
COPD	4918	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
COPD	4919	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
COPD	492	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities

Condition to identify	ICD-9-CM code or HCPCs code	Source
COPD	4928	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
COPD	494	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
COPD	4940	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
COPD	4941	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
COPD	496	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	36211	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	4010	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	4011	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	4019	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40200	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40201	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40210	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40211	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40290	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40291	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40300	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40301	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40310	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40311	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	4039	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40391	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40400	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40401	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40402	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40403	CMS Chronic Condition Warehouse and

Condition to identify	ICD-9-CM code or HCPCs code	Source
		Elixhauser/HCUP comorbidities
Hypertension	40410	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40411	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40412	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40413	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40490	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40491	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40492	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40493	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40501	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40509	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40511	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40519	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40591	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	40599	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	4372	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	64210	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	64211	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	64212	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	64213	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	64214	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	64200	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	64201	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	64202	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Hypertension	64203	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities

Condition to identify	ICD-9-CM code or HCPCs code	Source
Hypertension	64204	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	39891	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	4280	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	4281	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	4282	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	42820	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	42821	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	42822	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	42823	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	4283	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	42830	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	42831	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	42832	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	42833	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	4284	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	42840	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	42841	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	42842	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	42843	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Congestive Heart Failure	4289	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Prenatal care	CPT 5430	Texas Medicaid provider procedures manual
Prenatal care	CPT 99201 Mod TH	Texas Medicaid provider procedures manual
Prenatal care	CPT 99202 Mod TH	Texas Medicaid provider procedures manual
Prenatal care	CPT 99203 Mod TH	Texas Medicaid provider procedures manual
Prenatal care	CPT 99204 Mod TH	Texas Medicaid provider procedures manual
Prenatal care	CPT 99205 Mod TH	Texas Medicaid provider procedures manual
Prenatal care	CPT 99211 Mod TH	Texas Medicaid provider procedures manual
Prenatal care	CPT 99212 Mod TH	Texas Medicaid provider procedures manual
Prenatal care	CPT 99213 Mod TH	Texas Medicaid provider procedures manual

Condition to identify	ICD-9-CM code or HCPCs code	Source
Prenatal care	CPT 99214 Mod TH	Texas Medicaid provider procedures manual
Prenatal care	CPT 99215 Mod TH	Texas Medicaid provider procedures manual
Prenatal care	0500F	Blue Cross/ Blue Shield coding advice
Prenatal care	0501F	Blue Cross/ Blue Shield coding advice
Prenatal care	0502F	Blue Cross/ Blue Shield coding advice
Dehydration	2765	AHRQ Tech Specs
Dehydration	27650	AHRQ Tech Specs
Dehydration	27651	AHRQ Tech Specs
Dehydration	27652	AHRQ Tech Specs
Dehydration	2760	AHRQ Tech Specs
Dehydration	00861	AHRQ Tech Specs
Dehydration	00862	AHRQ Tech Specs
Dehydration	00863	AHRQ Tech Specs
Dehydration	00864	AHRQ Tech Specs
Dehydration	00865	AHRQ Tech Specs
Dehydration	00866	AHRQ Tech Specs
Dehydration	00867	AHRQ Tech Specs
Dehydration	00869	AHRQ Tech Specs
Dehydration	0088	AHRQ Tech Specs
Dehydration	0090	AHRQ Tech Specs
Dehydration	0091	AHRQ Tech Specs
Dehydration	0092	AHRQ Tech Specs
Dehydration	0093	AHRQ Tech Specs
Dehydration	5589	AHRQ Tech Specs
Bacterial Pneumonia	481	AHRQ Tech Specs
Bacterial Pneumonia	4822	AHRQ Tech Specs
Bacterial Pneumonia	48230	AHRQ Tech Specs
Bacterial Pneumonia	48231	AHRQ Tech Specs
Bacterial Pneumonia	48232	AHRQ Tech Specs
Bacterial Pneumonia	48239	AHRQ Tech Specs
Bacterial Pneumonia	48241	AHRQ Tech Specs
Bacterial Pneumonia	48242	AHRQ Tech Specs
Bacterial Pneumonia	4829	AHRQ Tech Specs
Bacterial Pneumonia	4830	AHRQ Tech Specs
Bacterial Pneumonia	4831	AHRQ Tech Specs
Bacterial Pneumonia	4838	AHRQ Tech Specs
Bacterial Pneumonia	485	AHRQ Tech Specs
Bacterial Pneumonia	486	AHRQ Tech Specs
Urinary Tract Infection	59010	AHRQ Tech Specs
Urinary Tract Infection	59011	AHRQ Tech Specs
Urinary Tract Infection	5902	AHRQ Tech Specs
Urinary Tract Infection	5903	AHRQ Tech Specs
Urinary Tract Infection	59080	AHRQ Tech Specs
Urinary Tract Infection	59081	AHRQ Tech Specs
Urinary Tract Infection	5909	AHRQ Tech Specs
Urinary Tract Infection	5950	AHRQ Tech Specs
Urinary Tract Infection	5959	AHRQ Tech Specs
Urinary Tract Infection	5990	AHRQ Tech Specs

Condition to identify	ICD-9-CM code or HCPCs code	Source
Asthma	493	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Asthma	49301	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Asthma	49302	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Asthma	4931	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Asthma	49311	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Asthma	49312	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Asthma	4932	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Asthma	49321	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Asthma	49322	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Asthma	49381	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Asthma	49382	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Asthma	4939	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Asthma	49391	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Asthma	49392	CMS Chronic Condition Warehouse and Elixhauser/HCUP comorbidities
Angina	4111	AHRQ Tech Specs
Angina	41181	AHRQ Tech Specs
Angina	41189	AHRQ Tech Specs
Angina	4130	AHRQ Tech Specs
Angina	4131	AHRQ Tech Specs
Angina	4139	AHRQ Tech Specs
Coronary Artery bypass procedure	36.10	CDC Surgical Site Infection Table
Coronary Artery bypass procedure	36.11	CDC Surgical Site Infection Table
Coronary Artery bypass procedure	36.12	CDC Surgical Site Infection Table
Coronary Artery bypass procedure	36.13	CDC Surgical Site Infection Table
Coronary Artery bypass procedure	36.14	CDC Surgical Site Infection Table
Coronary Artery bypass procedure	36.15	CDC Surgical Site Infection Table
Coronary Artery bypass procedure	36.16	CDC Surgical Site Infection Table
Coronary Artery bypass	36.17	CDC Surgical Site Infection Table

Condition to identify	ICD-9-CM code or HCPCs code	Source
procedure		
Coronary Artery bypass procedure	36.19	CDC Surgical Site Infection Table
Coronary Artery bypass procedure	36.2	CDC Surgical Site Infection Table
Hip prosthetic procedure	00.70	CDC Surgical Site Infection Table
Hip prosthetic procedure	00.71	CDC Surgical Site Infection Table
Hip prosthetic procedure	00.72	CDC Surgical Site Infection Table
Hip prosthetic procedure	00.73	CDC Surgical Site Infection Table
Hip prosthetic procedure	00.85	CDC Surgical Site Infection Table
Hip prosthetic procedure	00.86	CDC Surgical Site Infection Table
Hip prosthetic procedure	00.87	CDC Surgical Site Infection Table
Hip prosthetic procedure	81.51	CDC Surgical Site Infection Table
Hip prosthetic procedure	81.52	CDC Surgical Site Infection Table
Hip prosthetic procedure	81.53	CDC Surgical Site Infection Table
Knee prosthetic procedure	00.80	CDC Surgical Site Infection Table
Knee prosthetic procedure	00.81	CDC Surgical Site Infection Table
Knee prosthetic procedure	00.82	CDC Surgical Site Infection Table
Knee prosthetic procedure	00.83	CDC Surgical Site Infection Table
Knee prosthetic procedure	00.84	CDC Surgical Site Infection Table
Knee prosthetic procedure	81.54	CDC Surgical Site Infection Table
Knee prosthetic procedure	81.55	CDC Surgical Site Infection Table
SSI	51920 and one of procs 03610-03619	McNutt, 2010
SSI	8942	Sherman, 2006; Stevenson2008
SSI	99661	Sherman, 2006; Stevenson2008
SSI	99662	Sherman, 2006; Stevenson2008
SSI	99663	Sherman, 2006; Stevenson2008
SSI	99666	Sherman, 2006; Stevenson2008
SSI	99667	Sherman, 2006; Stevenson2008
SSI	99671	Sherman, 2006; Stevenson2008
SSI	99672	Sherman, 2006; Stevenson2008
SSI	9980	Sherman, 2006; Stevenson2008
SSI	99831	Sherman, 2006; Stevenson2008
SSI	99832	Sherman, 2006; Stevenson2008
SSI	99851	Sherman, 2006; Stevenson2008
SSI	99859	Sherman, 2006; Stevenson2008
SSI	9986	Sherman, 2006; Stevenson2008
SSI	99883	Sherman, 2006; Stevenson2008
SSI	9993	Sherman, 2006; Stevenson2008
SSI	32081	Sherman, 2006; Stevenson2008
SSI	32082	Sherman, 2006; Stevenson2008

Condition to identify	ICD-9-CM code or HCPCs code	Source
SSI	32089	Sherman, 2006; Stevenson2008
SSI	3200	Sherman, 2006; Stevenson2008
SSI	3201	Sherman, 2006; Stevenson2008
SSI	3202	Sherman, 2006; Stevenson2008
SSI	3203	Sherman, 2006; Stevenson2008
SSI	3207	Sherman, 2006; Stevenson2008
SSI	3209	Sherman, 2006; Stevenson2008
SSI	3210	Sherman, 2006; Stevenson2008
SSI	3211	Sherman, 2006; Stevenson2008
SSI	3212	Sherman, 2006; Stevenson2008
SSI	3213	Sherman, 2006; Stevenson2008
SSI	3214	Sherman, 2006; Stevenson2008
SSI	3218	Sherman, 2006; Stevenson2008
SSI	3220	Sherman, 2006; Stevenson2008
SSI	3221	Sherman, 2006; Stevenson2008
SSI	3222	Sherman, 2006; Stevenson2008
SSI	3229	Sherman, 2006; Stevenson2008
SSI	3240	Sherman, 2006; Stevenson2008
SSI	3241	Sherman, 2006; Stevenson2008
SSI	3249	Sherman, 2006; Stevenson2008
SSI	42090	Sherman, 2006; Stevenson2008
SSI	42091	Sherman, 2006; Stevenson2008
SSI	42099	Sherman, 2006; Stevenson2008
SSI	4219	Sherman, 2006; Stevenson2008
SSI	42290	Sherman, 2006; Stevenson2008
SSI	42291	Sherman, 2006; Stevenson2008
SSI	5131	Sherman, 2006; Stevenson2008
SSI	5192	Sherman, 2006; Stevenson2008
SSI	6821	Sherman, 2006; Stevenson2008
SSI	6822	Sherman, 2006; Stevenson2008
SSI	6823	Sherman, 2006; Stevenson2008
SSI	6824	Sherman, 2006; Stevenson2008
SSI	6826	Sherman, 2006; Stevenson2008
SSI	6827	Sherman, 2006; Stevenson2008
SSI	6829	Sherman, 2006; Stevenson2008
SSI	7280	Sherman, 2006; Stevenson2008
SSI	73000	Sherman, 2006; Stevenson2008
SSI	73001	Sherman, 2006; Stevenson2008
SSI	73002	Sherman, 2006; Stevenson2008
SSI	73003	Sherman, 2006; Stevenson2008
SSI	73004	Sherman, 2006; Stevenson2008
SSI	73005	Sherman, 2006; Stevenson2008
SSI	73006	Sherman, 2006; Stevenson2008
SSI	73007	Sherman, 2006; Stevenson2008
SSI	73008	Sherman, 2006; Stevenson2008
SSI	73009	Sherman, 2006; Stevenson2008
SSI	73020	Sherman, 2006; Stevenson2008
SSI	73021	Sherman, 2006; Stevenson2008

Condition to identify	ICD-9-CM code or HCPCs code	Source
SSI	73022	Sherman, 2006; Stevenson2008
SSI	73023	Sherman, 2006; Stevenson2008
SSI	73024	Sherman, 2006; Stevenson2008
SSI	73025	Sherman, 2006; Stevenson2008
SSI	73026	Sherman, 2006; Stevenson2008
SSI	73027	Sherman, 2006; Stevenson2008
SSI	73028	Sherman, 2006; Stevenson2008
SSI	73029	Sherman, 2006; Stevenson2008
SSI	73030	Sherman, 2006; Stevenson2008
SSI	73031	Sherman, 2006; Stevenson2008
SSI	73032	Sherman, 2006; Stevenson2008
SSI	73033	Sherman, 2006; Stevenson2008
SSI	73034	Sherman, 2006; Stevenson2008
SSI	73035	Sherman, 2006; Stevenson2008
SSI	73036	Sherman, 2006; Stevenson2008
SSI	73037	Sherman, 2006; Stevenson2008
SSI	73038	Sherman, 2006; Stevenson2008
SSI	73039	Sherman, 2006; Stevenson2008
SSI	73090	Sherman, 2006; Stevenson2008
SSI	73091	Sherman, 2006; Stevenson2008
SSI	73092	Sherman, 2006; Stevenson2008
SSI	73093	Sherman, 2006; Stevenson2008
SSI	73094	Sherman, 2006; Stevenson2008
SSI	73095	Sherman, 2006; Stevenson2008
SSI	73096	Sherman, 2006; Stevenson2008
SSI	73097	Sherman, 2006; Stevenson2008
SSI	73098	Sherman, 2006; Stevenson2008
SSI	73099	Sherman, 2006; Stevenson2008
SSI	8900	Sherman, 2006; Stevenson2008
SSI	8901	Sherman, 2006; Stevenson2008
SSI	8902	Sherman, 2006; Stevenson2008
SSI	8910	Sherman, 2006; Stevenson2008
SSI	8911	Sherman, 2006; Stevenson2008
SSI	8912	Sherman, 2006; Stevenson2008
SSI	8940	Sherman, 2006; Stevenson2008
SSI	8941	Sherman, 2006; Stevenson2008
CAUTI	996.64	McNutt, 2010
CAUTI	59000	Sherman, 2006
CAUTI	59001	Sherman, 2006
CAUTI	59010	Sherman, 2006
CAUTI	59011	Sherman, 2006
CAUTI	5902	Sherman, 2006
CAUTI	5903	Sherman, 2006
CAUTI	59080	Sherman, 2006
CAUTI	5909	Sherman, 2006
CAUTI	5950	Sherman, 2006
CAUTI	5951	Sherman, 2006
CAUTI	5952	Sherman, 2006

Condition to identify	ICD-9-CM code or HCPCs code	Source
CAUTI	5953	Sherman, 2006
CAUTI	59581	Sherman, 2006
CAUTI	59589	Sherman, 2006
CAUTI	5959	Sherman, 2006
CAUTI	5990	Sherman, 2006
CAUTI	9975	Sherman, 2006
CAUTI	59081	ahrq PQI 12
CAUTI	996.31	icd9.chrisenders.com
CAUTI	57.94	icd9.chrisenders.com
CAUTI	97.64	icd9.chrisenders.com
VAP	4800	Sherman, 2006
VAP	31.1	Stevenson, 2008
VAP	31.2	Stevenson, 2008
VAP	31.21	Stevenson, 2008
VAP	31.29	Stevenson, 2008
VAP	9601	Restrepo,2010
VAP	9602	Restrepo,2010
VAP	9603	Restrepo,2010
VAP	9604	Restrepo,2010; Stevenson, 2008
VAP	9605	Restrepo,2010
VAP	9670	Restrepo,2010; Stevenson, 2008
VAP	9671	Restrepo,2010; Stevenson, 2008
VAP	9672	Restrepo,2010; Stevenson, 2008
VAP	4801	Sherman, 2006
VAP	4802	Sherman, 2006
VAP	4803	Sherman, 2006
VAP	4808	Sherman, 2006
VAP	4809	Sherman, 2006
VAP	481	Sherman, 2006
VAP	4820	Sherman, 2006
VAP	4821	Sherman, 2006
VAP	4822	Sherman, 2006
VAP	48230	Sherman, 2006
VAP	48231	Sherman, 2006
VAP	48232	Sherman, 2006
VAP	48239	Sherman, 2006
VAP	48240	Sherman, 2006
VAP	48241	Sherman, 2006
VAP	48249	Sherman, 2006
VAP	48281	Sherman, 2006
VAP	48282	Sherman, 2006
VAP	48283	Sherman, 2006
VAP	48284	Sherman, 2006
VAP	48289	Sherman, 2006
VAP	4829	Sherman, 2006
VAP	4830	Sherman, 2006
VAP	4831	Sherman, 2006
VAP	4838	Sherman, 2006

Condition to identify	ICD-9-CM code or HCPCs code	Source
VAP	485	Sherman, 2006
VAP	486	Sherman, 2006
VAP	4870	Sherman, 2006